PHD

# Advanced methods for the analysis of performance and injury in elite soccer

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# ADVANCED METHODS FOR THE ANALYSIS OF PERFORMANCE AND INJURY IN ELITE SOCCER


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# ABSTRACT


**Advanced methods for the analysis of performance and injury in elite soccer**

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In elite soccer, monitoring training and match load using Global Navigation Satellite System (GNSS) devices is well established and provides insight to assist practitioners to plan training that optimises performance and minimises injury risk. The influx in available GNSS data enables practitioners and researchers to more easily interrogate data and push the boundaries of performance. However, it also introduces communication challenges to provide coaches with succinct messages to effect training decisions. This thesis aims to investigate the applicability of GNSS devices to accurately provide data and instigate the subsequent analysis process to provide insight to the association between training load, injury and performance.

Results showed position tracking devices to acceptably measure team-sport specific movement with caution recommended when measuring high complexity movements. This element of the thesis was carried out early in the PhD and the author notes that providers can now externally certify accuracy through FIFA standardised testing.

Training load data from an English Premier League club was contextualised using a match data reference method and then simplified using dimensionality reduction which identified three pertinent components of training load. This methodology was used using data from Australian A-League soccer players and showed that conscious manipulation of training loads over an extended multi-season period may be able to influence team injury rates in professional soccer. Analysis on the same group of player across the same time period showed that training load did not offer any additional insight into performance estimation over simple forecasting models. Additionally, none of the models within the study performed well enough to be a useful practical tool to predict performance.

This research offers insight into training analysis techniques and applied case studies of load, providing practitioners with examples of how to manipulate GNSS data for effective use to inform strategic decisions.

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# CHAPTER 1: INTRODUCTION

'Football as we know it' describes the establishment of the original rules of association football, commonly known as soccer, by the United Kingdom Football Association in 1863 (FIFA, 2018). Soccer is the most popular sport worldwide, with an estimated 500 million players (Krustrup and Krustrup, 2018) including 300 million formally registered with clubs (Kahn et al., 2012).

A key reason for the popularity of soccer is its simplicity to participate - a ball and flat area offer the simple backdrop for anyone across the world to play. Football associations publish the laws of the game which establish pitch dimensions, ball size and officiating. The standardised laws of the game have created a multi-tiered competitive system across the world culminating in the most globally viewed sport, with over 3.5 billion fans watching the 2014 world cup matches on television (Huffingtonpost.com, 2018).

Success for elite soccer is measured through various metrics including fan popularity, commercial power and financial profit margin but the ultimate measure of success, impacting all other areas, is the ability to win respective local and international competitions. Soccer economics is a widely researched subject (Dabscheck, 2010; Littlewood, 2015) that shows the magnitude and significance of finance within the industry. Elite clubs collect substantial revenues from commercial partners and television rights which in turn, have increased player salaries and transfer fees. The English Premier League (EPL) television rights (2016-2019) were sold for £8.4 billion, a contributing factor to what is the richest league in the world (Guardian.com, 2017). The increase in monies available to clubs mean that players have become expensive assets and investment in their well-being and performance has grown substantially. It was apparent that the industry could no longer rely on the traditional methods of previous decades (Reilly, 2007), contributing to a significant shift towards sports science as a field to support the development of elite players for fitness, strength, nutrition, workload and recovery (Kennedy and Kennedy, 2016) in order to maximise output.

The field of sports science dates back to the pioneering work of Hill, Meyerhof and Kroch who shared the 1922 Nobel prize for their work on muscular exercise (Powers and Howley, 2012). There has been a remarkable expansion in sports science as an academic discipline and field of applied practice (Reilly and Williams, 2003). Throughout the 20th and 21st centuries; universities, sports teams and elite athletes have explored innovative research and applied recommendations to maximise human performance. The close relationship between research and applied environment within elite clubs has facilitated the use of multi-disciplinary performance teams to utilise knowledge gained to enhance player physical performance. The development of soccer-specific scientific research was buoyed by the introduction of the

World Congress of Science and Football in 1987 (Reilly and Williams, 2003). Since then, boundaries have been pushed across various disciplines including physiology, performance analysis, biomechanics and pedagogy.

The significant changes in the modern game style and physical output (Barnes et al., 2014) reflect the knowledge gained from experience and research to change training practices ensuring players can produce high performance outputs across fifty-plus matches per season (Walker and Hawkins, 2018). This thesis aims to continue to bridge the gap between research and applied practice - it is the author's opinion that the relationship can be embraced both ways - practitioners should continuously review their practice to ensure their work is scientifically supported and equally there is a need for research in applied work to drive the industry forward.

The focus throughout this thesis is the monitoring of player workload, specifically through the use of Global Navigation Satellite System (GNSS) technology. Workload in sport is defined as the cumulative amount of stress placed on an individual from single or multiple training sessions and matches (Soligard et al., 2016; Eckard et al., 2018). Whilst this definition is specific to physical loads, it is important to acknowledge other types of loads that are imperative to understanding athlete performance (e. g. psychological and social). The increased use of GNSS devices has led to increased access to data for applied practitioners (Aughey, 2011); however, this presents challenges with data complexity and subsequent issues with presentation to coaches and players. It is critical for practitioners to process data effectively to make meaningful inferences on the training process and importantly, present to coaches to ultimately improve performance and reduce the risk of any adverse effect of training and match-play (Bourdon et al., 2017).

A major adverse effect of training and match workload is injury, which is defined in soccer as *'any physical complaint sustained by a player that results from a football match or football training, irrespective of the need for medical attention or time loss from football activities. An injury that results in a player receiving medical attention is referred to as a ''medical attention'' injury, and an injury that results in a player being unable to take a full part in future football training or match play as a ''time loss'' injury' (*Fuller et al., 2006*).* Injury typically impacts player availability for matches, subsequently impacting team selection continuity (Hagglund, Walden and Ekstrand, 2013); this has substantial financial implications (Gallo et al., 2006*)* and is ultimately associated with team performance (Árnason et al., 2004; Eirale et al., 2013; Hagglund et al., 2013b).

With the exponential rise in available data, practitioners require simple methods of monitoring, interpreting and presenting information. Exploring the methods and the subsequent association of load, injury and performance in soccer is the foundation of this research. The current thesis aims to:

- Investigate the applicability of GNSS devices to accurately provide data and the subsequent methods to provide simple and contextualised information supporting informed decisions to improve elite soccer performance.
- Analyse longitudinal training and match data in elite soccer to provide insight into association with injury and performance.

To investigate these aims, this thesis will:

1. Assess the validity of GPS devices to measure the distance of team-sport specific movement
2. Provide context to training load data and simplify the description of training by identifying pertinent metrics
3. Provide insight into the statistical analysis of training load used in elite teams
4. Analyse the influence of training load on the risk of injury in elite soccer players
5. Establish whether an existing metric is appropriate to measure individual match performance
6. Analyse the influence of multiple factors, including training load, to assess the subsequent success to predict performance

# CHAPTER 2: LITERATURE REVIEW

## *2.1 Introduction*

This review will firstly provide a synopsis of the body of literature exploring the physical demands and physiological requirements of a soccer match and present the technologies used to measure athletic movement. A key theme throughout will consider how research is linked to the applied environment and how outcomes affect day-to-day decisions of coaches and performance staff to improve player performance. Specific reference will be given to the use of Global Navigation Satellite System (GNSS) technology through an analysis of the validity and reliability as well as discussing the challenges met and advances made in elite sport today.

Interest in research investigating athlete training load has increased in recent years (Halson, 2014); however, much of what is utilised still comes from personal experience, anecdotal information and remains unpublished (Bourdon et al., 2017). This research will be discussed with consideration of the definition of load, categorising load metrics and how these are analysed and modelled to facilitate coach decision-making.

There has been considerable research exploring the relationship between training load and injury (Eckard et al., 2018). An appreciation of the physiological profile of soccer players, the match demands of the sport and an exploration into the injury epidemiology research in elite soccer provides an overview to this subject, including an appreciation of the potential association to injury risk. Injury risk modelling explores how data analysis is used to investigate training load and injury patterns to predict injury and help inform load planning. Current research on injury risk modelling will be evaluated to explore the power and effectiveness of these monitoring technologies and the subsequent data analyses. Gaps and inefficiencies in the analysis process or practices will also be addressed.

Performance responses to training are influenced by a myriad of training and non-training related factors and are difficult to accurately predict (Bourdon et al., 2017). Methods of measuring elite soccer performance will be considered and a review of the data analysis techniques used to predict performance evaluated.

## *2.2 Match analysis in elite soccer*

### *2.2.1 Match analysis technology*

The study of motion analysis has been applied in soccer for over 30 years (Reilly and Thomas, 1976). Traditional methods utilised video cameras to analyse individual players with researchers coding footage from match playback to quantify physical and technical actions (Carling et al., 2008). These time-consuming methods were replaced by superior video technology where footage was digitised and synchronised from manual to automatic coding which automatically calculates movement activities. These methods, although detailed, continued to be time consuming and laborious (Bloomfield, Polman and O'Donoghue, 2007). Technological advancement has led to the development of electronic systems including automatic video tracking, local positioning measurement and GNSS (Cardinale, 2006; Linke et al., 2018; Beato et al., 2018).

Thomas Reilly predicted 'as sport and exercise grew in popularity and commercial impact, they are increasingly influenced by modern technology, novel applications of science being promoted to help solve some of the questions presented by intense activity, and to enhance performance' (Reilly and Williams, 2003). Figure 2.1 shows the influx of studies published by the *Journal of Sports Sciences,* a journal with a strong history of publishing applied research in soccer, linked to the onset of available data from emerging technologies (Coutts, 2014).

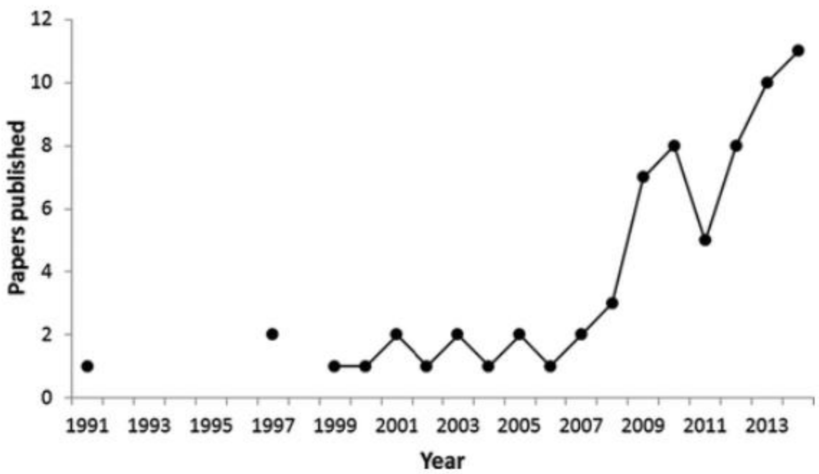



*Figure 2.1 Football match and training analysis papers published in the Journal of Sports Sciences presented in 'Evolution of football match analysis research' (Coutts, 2014)*

GNSS data collected by electronic performance and tracking systems (EPTS) has been available to performance departments in elite sport since the early 21st century and FIFA sanctioned the use of EPTS in competitive match-play in 2015 (FIFA, 2019). GNSS technology has evolved in multiple ways, fuelled by the hunger from elite clubs for devices that are smaller, lighter and more accurate.

*2.2.2 The physical profile of elite soccer*

When designing a training programme for any sport, the first priority is to identify the physical demands and match to the skill abilities which an athlete needs to be successful. A common pitfall when performing this type of analysis is to simply describe the sport's physical demands

(Cleather, 2018). Incorporating knowledge of the physiological requirements of elite soccer players can help practitioners design training strategies and therefore maximise performance potential.

Time-motion analysis characterises soccer as high intensity, intermittent, non-continuous exercise that varies across playing position, competition level, country, team playing style and has elicited longitudinal physical demand shifts (Ekblom, 1986; Carling, Williams and Reilly, 2005). More recently, analysis shows soccer is characterised by brief bouts of high-intensity linear and multidirectional activity interspersed with longer, variable recovery periods (Varley, Gabbett and Aughey, 2013). No criterion measure to distinguish physical performance in elite soccer matches has been identified but the total distance (m) covered to represent volume and subsequent breakdown into speed bands to represent intensity are useful initial indicators (Krustrup et al., 2018). Recent research also explores high-velocity movement along with acceleration in a bid to understand the high-intensity movement patterns of players during competition (Varley, Gabbett and Aughey, 2013). There is a consensus in sport science that effective training should closely replicate competitive performance conditions; therefore, training prescriptions in soccer should be based on the specific requirements of the playing positions (Di Salvo et al., 2007).

Distance covered is used as an indicator of volume of work completed and can provide a crude representation of energy expenditure, shaping work-to-rest ratios and intensities of play (Bloomfield, Poleman and O'Donoghue, 2007). It is well researched that outfield players cover on average between 9,000 and 12,000 m during a full soccer match (Ekblom, 1986; Stolen et al., 2005; Bangsbo, Mohr and Krustrup, 2006; Di Salvo et al., 2007; Bradley, 2009). A soccer training programme is designed to allow a player to be able to cope with this volume without the adverse effects of fatigue.

Midfield players cover significantly more distance ($p < 0.0001$) than both defenders and forwards with central defenders covering on average the least (Di Salvo et al., 2007), a trend which is in agreement with other studies (Ekblom, 1986; Bangsbo,1994; Bloomfield, Poleman and O'Donoghue, 2007; Bradley, 2013). Central defenders were shown to cover significantly less ($p < 0.0001$) distance than any other outfield position in a study assessing elite players competing in the European Champions League (Di Salvo et al., 2007). Positional variations, whilst maintaining importance on preparing players to cope with the full volume of a soccer match, provide specific physical information about each position and its demands, which could impact individual programming.

Total distance covered does not holistically illustrate the work rate profiles of soccer athletes (Reilly, 1997). Analysis of distance covered within specific speed zones broadens the activity profile analysis and can further inform and direct training design and prescription. Player activities are coded by research studies into speed thresholds for example; standing (0–0.6 km.h-1), walking (0.7–7.1 km.h-1), jogging (7.2–14.3 km.h-1), running (14.4–19.7 km.h-1), high-speed running (19.8–25.1 km.h-1), and sprinting (>25.1 km.h-1) (Bangsbo, 1994; Mohr, Krustrup and Bangsbo, 2003; Rampinini et al., 2007; Bradley, 2009). These thresholds, albeit common, are not universal, so caution is advised when comparing research data. In the applied environment, the use of changeable intensity thresholds will have an impact on comparative analysis.

English Premier League players accumulate on average 350 ± 139 m (>25.1 km.hr$^{-1}$) of sprint distance and 1151 ± 337 m of high-intensity running distance (>19.8 km.hr$^{-1}$) (Barnes et al., 2014). These high-intensity running zones are of interest to practitioners as they correlate well with physical capacity (Bradley, 2011) and hamstring injury risk (Duhig et al., 2016). Central defenders cover the lowest distance at high intensity (>19.8 km.hr-1) and spend significantly more time ($p < 0.0001$) walking and jogging (0–11 km/h) (Di Salvo et al., 2007). The same study, analysing data from the European Champions League, revealed both wide midfield and wide defender positions complete more sprints than corresponding central formations. The capability to execute bouts of high intensity exercise repeatedly during a match is of major importance in soccer (Bangsbo, 1994) and the data informing practitioners of positional variation can shape the individualisation of training programmes to improve match output and reduce the risk of injury.

Technological advancement has allowed researchers to investigate the output and demands of the change of speed and direction. Physical testing shows a high correlation between maximal acceleration and maximal velocity; however, research has shown there is a need to distinguish between these physical metrics as during match-play a player is not always required to maximally accelerate to achieve maximal velocity, and performing a maximal acceleration will not always lead to maximal or high-velocity running (Varley and Aughey, 2013). Additionally, soccer players undertake an 8-fold greater number of accelerations than sprints during match-play (Varley and Aughey, 2013). Performing an acceleration from a lower velocity can match or even exceed the power output required to maintain a higher velocity (Osgnack et al., 2010) and high levels of accelerations in matches and training over a 4-week period can lead to a significant increase in the risk of injury (RR=3.84, 95% CI 1.57 to 9.41, $p=0.003$) (Bowen et al., 2017). The number of maximal accelerations was homogenous across all outfield positions with the exception of wide defenders who performed the greatest number of maximal accelerations and low velocity accelerations across all playing periods ($P < 0.006$ and $P < 0.001$ respectively) (Varley and Aughey, 2013). This could be due to wide defenders often being required to perform both defensive and offensive duties resulting in constant back and forth movement which may explain the high number of accelerations and sprints undertaken.

Other actions performed during match play contributing to total energy expenditure include heading, blocking (Bloomfield, Poleman and O'Donoghue, 2007), tackling, jumping (Bangsbo, Mohr and Krustrup, 2006) kicking and dribbling (Bangsbo, 1994). The exertional cost from dribbling a soccer ball has been reported at 5.2 kJ·min-1 (Reilly and Gilbourne, 2003) and alongside time-motion information, these actions need to be acknowledged when planning training programmes to prepare players for regular match exposure.

An appreciation of the physiological requirements of elite soccer players can help practitioners design training strategies. It has been shown that it is beneficial for elite players to have a high $VO^2$max, typically between 55 and 65 $ml.kg.min^{-1}$ (Bangsbo, 1994, Magalhaes Salas et al., 2001); have high anaerobic capacities to perform the high-speed actions impacting on soccer performance (Little and Williams, 2005) (peak lactate levels of 14 mmol.L-1 have been recorded during a match) (Stolen et al., 2005); and show high levels of a range of strength based physical qualities including acceleration, maximal speed and agility (Little et al., 2005). Knowledge of the physiological and biomechanical factors that determine performance will allow specific training programmes to be designed to address player weaknesses, and ultimately, to improve match performance (Little et al., 2005).

### *2.2.3 The trends of physical profile in elite soccer*

Soccer has been described as stochastic, intermittent, acyclical, variable and unpredictable (Nicholas et al., 2000). Physical profiles can vary between playing position, competition level and change longitudinally (Carling et al., 2008).

There is a general trend that a higher standard of soccer elicits a higher intensity output of physical work with European Champions League players eliciting significantly higher high-intensity running and sprint distances than Danish top league players ($p < 0.05$). In addition, Champions League teams cover more total distance and high-intensity running (19.8 to 25.2 $km.h^{-1}$) when playing against top ranked teams compared to teams in lower leagues ($p < 0.05$).

A second trend is the evolution of physical output and how the modern-day soccer match is played very differently. Distance covered (m) in the English Premier League was relatively constant between 2006-07 (10679 ± 956 m) and 2012-13 (10881 ± 885 m); however, there was a clear increase in high-intensity distance (m > 19.8 $km.h^{-1}$) 890 ± 299 m to 1151 ± 337 m ($p < 0.001$, ES 0.82) in the same period (Barnes et al., 2014). Sprinting (m > 25.1 $km.h^{-1}$) also increased by ~35%, attributed to more frequent shorter sprints completed. These data suggest current players can produce higher intensity actions on a more consistent basis.

Therefore, the preparation and training of players should be appropriately designed to allow for pre-conditioning of these actions.

Cultural differences may exist across professional soccer leagues and playing positions. There were significant differences reported for high-intensity running (m > 19.8 $km.h^{-1}$) between English Premier League (EPL) and Spanish La Liga players irrespective of playing position (Dellal et al., 2011). This and further data from this study, highlight the cultural differences in performance which may have an impact on transfers to different leagues, as they suggest that players moving between countries need to adapt both physically and technically (Dellal et al., 2011).

These data provide feedback on physical performance and trends which practitioners can subsequently evaluate, interpret and eventually transform into informed planning. Effective training should closely replicate competitive performance conditions and therefore training prescriptions in soccer should be based on the specific requirements of the playing positions (Di Salvo et al., 2007). As well as training intervention and planning, knowledge of the physical demands and requirements is being used to objectively identify key performance indicators to then be used during the scouting and recruitment process (Barron et al., 2014).

## *2.3 Technology measuring athletic movement*

### *2.3.1 Introduction*

This section will look specifically at the evolution of satellite technology to measure position, from the development of the American Global Positioning System (GPS) through to current collaborative GNSS. Further to this, the use of this technology for measuring human locomotion, particularly the developments to track soccer actions in training and match play will be outlined. Additionally, the accuracy of the systems involved is discussed and the validity and reliability of specific devices to measure sports specific movement will be closely scrutinised.

### *2.3.2 Evolution of satellite positioning technology*

Early navigation system developments through the 1960s and 1970s produced varying degrees of accuracy and usability. These developments culminated in the U.S. Department of Defense funding the first global satellite system in 1973, now known as the global positioning system (GPS). This US-managed navigation system used 27 satellites, each housing an atomic clock to provide timing accuracy to within a nanosecond (Theiss, Yen and Ku, 2005). As of October 17, 2017, there were thirty-one operational satellites in the GPS constellation, not including the decommissioned or on-orbit spares and the US Government is committed to maintaining the availability of at least 24 operational satellites, 95% of the time (US Government, 2018). Originally developed for military use, now increasingly used for aviation, marine and recreational outdoor purposes (Larsson, 2003), GPS has been adopted in sports settings to collect training load data using integrated devices combining accelerometers, gyroscopes and global position receiving chips (Dellaserra *et al*., 2014).

GPS consists of a space segment of operational satellites, a control segment (a series of ground facilities to monitor the operation of the space segment) and a user segment consisting of hardware and processing software needed to measure location (Pace, 1996). Satellites have a life goal of 7.5 years and are therefore replaced regularly to maintain operational numbers. Housing atomic clocks (2 rubidium and 2 cesium), the satellites are solar powered and constantly adjust their orientation to ensure panels face the sun and antennas face the earth. The control segment consists of special monitoring systems which receive signals from the satellites and subsequently update orbital information hourly. The associated ground segment is used to minimise error that accompanies positioning systems (Blewitt, 1997)

The GPS signal starts in the satellite as a voltage which oscillates at the fundamental clock frequency of 10.23 Mhz. After frequency multiplication, the L1 and L2 carrier signals are transmitted as a stream of digits (linear feedback register sequence). Unique to each satellite, the C/A code (course acquisition code contained in L1 signal transmitted signal transmission time) and the P-Code (precise code contained in L1 and L2, a high resolution transmission time stamp) are bundled with the navigation message, boosted by an amplifier and sent towards earth where they pass through the earth's atmosphere to the receiver antenna (Blewitt,1997).

Satellite location data uses Cartesian coordinates in a geocentric system (Figure 2.2). Originating at the Earth centre of mass, Z-axis pointing towards the North Pole, X pointing towards the prime meridian (which crosses Greenwich, UK), and Y at right angles to X and Z to form a right-handed orthogonal coordinate system.

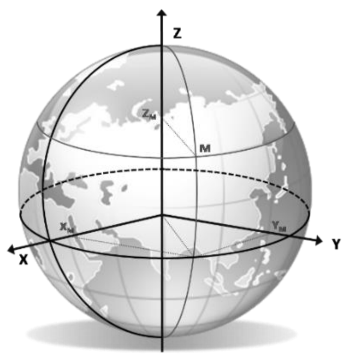


*Figure 2.2 Cartesian coordinates indicated by (X, Y, Z) used to compute satellite location (Royal Observatory of Belgium GNSS Research Group, Accessed September, 2019)*

The process of autocorrelation computes the time difference between the actual GPS signal and a replica signal (transmitted by the receiver). Figure 2.3 shows the crossover relationship between the two signals - this time difference (inferred time displacement between these two signals) is used to calculate what is known as a 'pseudorange' (Blewitt, 1997).

$$pseudorange = (T - Ts) \times (speed\ of\ light)$$

These simplified workings of the pseudorange calculation use T as the known reading of the receiver clock when signal is received and $T^S$ as the reading of the satellite clock when the signal was transmitted.

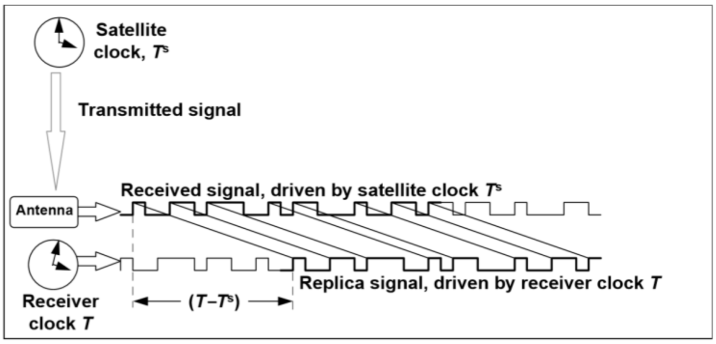



*Figure 2.3 Diagram showing the relationship between the two signal times during the GPS pseudorange calculation process (Blewitt, 1997)*

After accounting for clock bias (using 'differencing techniques') the receiver position (x, y, z) can be calculated using the pseudoranges from 4 satellites (Larsson, 2003; Terrier and Schutz, 2005). The dilution of precision (DOP) is used to describe the error for the various portions of location calculations - if fewer than four satellites are available then the DOP values are infinity and position dilution of precision (PDOP) values of 5 are considered poor. If DOP had a value of 5, pseudorange errors of 1 metre and vertical position errors of 5 metres are expected (Blewitt, 1997). Contributing to error, the quality of geodetic results present absolute (global) positioning at the level of 1 cm, tropospheric delay estimated to a few mm, GPS orbits determines to 10 cm, earth pole position determined to 1 cm and clock synchronisation (relative bias estimation) to 100 ps (Blewitt, 1997).

This explanation outlines the basics of GPS positioning observation models and parameter estimation citing the work presented by Geoffery Blewitt from the Department of Geomatics - University of Newcastle, (1997). Today, most receiver devices have accessibility to many more satellites due to the development of the global navigation satellite system (GNSS)

(Garzia et al., 2016). GNSS incorporates a constellation of orbiting satellites working in conjunction with a network of ground stations and each system is developed and managed by separate countries. Current operational systems are GPS (United States), the Global Navigation Satellite System (GLONASS - Russia), Galileo (European Union), the BeiDou Navigation Satellite System (BDS - China), and Indian Regional Navigation Satellite System (IRNSS - India) (Zimbelman and Keefe, 2017). GNSS receivers have become a common tool to assess players' physical activity during competition and training in team sports (Padulo et al., 2019), having the advantage to access multiple satellites, proving enhanced accuracy, redundancy and availability.

The rapid advancements of satellite technologies to measure activity in sport has led to a much deeper understanding of athlete activity profiles (Aughey, 2011) and allows investigations to be made into relationships between training load and outcomes like injury and performance. This data integration has allowed for an expanding field in data analytics within professional sports teams which will greatly develop the body of knowledge of athlete movement (Aughey, 2011).

### *2.3.2 Accuracy of satellite technology*

Advances in satellite position tracking technology have meant that the goal for GNSS is to achieve decimetre or centimetre level accuracy. Many factors contribute to increased position error which in turn impact the accuracy of training and match data. These error sources have guided the continuous development of GNSS devices to measure athlete movement.

Initial modernisation of GPS saw the intentional degradation of the GPS Standard Positioning Service known as selective availability, be discontinued on May 1, 2000 (Shaw, 2004). Since SA was discontinued, GPS users have routinely observed horizontal positioning accuracy values of less than 10 m. After selective availability, the next biggest contributor to positioning error is the signal delay caused by the earth's atmosphere. Ionospheric delay varies with solar activity, time of year, season, time of day and location. This makes it very difficult to predict how much ionospheric delay is impacting the calculated position. A receiver which is in a moving vehicle or where ionospheric scintillation (rapid temporal fluctuations in both amplitude and phase of trans-ionospheric GNSS signals caused by the scattering of irregularities in the distribution of electrons encountered along the radio propagation path) is present, may lose its ability to track incoming signals and take several minutes to recover the signal needed for precise positioning. The same is true when the receiver must view satellites through foliage or in the presence of multipath signals due to high buildings. Multipath is an error tied to satellite geometry which is due to the antenna also sensing signals from the satellite which reflect and refract from nearby objects which can be verified because observation residuals have a pattern that repeats every sidereal day (Blewitt, 1997). Ideal conditions for GNSS accuracy would be away from large buildings or foliage (topography) to reduce reflected signals. However, if this is not possible, access to additional coded signals will enable improved accuracy in sub-optimal environments and also through ionospheric corrections (Shaw, 2004).

The atomic clocks in the GNSS satellites are very accurate, but a small inaccuracy in the satellite clock results in a significant error in the position calculated by the receiver. For example, 10 nanoseconds of clock error results in 3 metres of position error (Hexagon Positioning Intelligence, 2019). Another source of inaccuracy derives from orbit error, where satellites vary from their normally very precise course. Continuously controlled and adjusted by the ground segment, orbit error can result in up to ±2.5 metres of position error. Other sources of inaccuracy include signal disruption due to weather/atmospheric conditions (tropospheric delay) and receiver quality (signals used, antenna quality and algorithms used) (Terrier and Schutz, 2005).

Resolving positioning error has been approached in different ways including the ability for GNSS receivers to handle multiple frequencies from multiple satellite constellations. As discussed, comparing the delays of two GNSS signals, L1 and L2, can correct the effect of ionospheric error (Hexagon Positioning Intelligence, 2019). Additionally, the development of GNSS compared to the original GPS has allowed access to multiple constellations operated by different countries, which also cover varying orbital space around the earth.

The use of differential GNSS (utilising a fixed, ground-based receiver) to determine the ranges to the satellites and to send correction signals to the receiver can enhance the precision of location positioning (Larsson, 2003), resolving the inaccuracies created by clock error. The NDGPS is an example of a differential GPS system operated by the U.S. Coast Guard Navigation Service consisting of a control centre and thirty-eight remote broadcast sites, aiming to improve the accuracy and integrity of GPS (US Department of Homeland Security, 2018).

Other large-scale, satellite-based augmentation systems improve the accuracy, reliability and availability of GNSS signals by transmitting wide-area error correction. Examples of these systems include wide area augmentation system (WAAS, Operated by the United States), the European Geostationary Navigation Overlay Service (EGNOS), MTSAT Satellite Based Augmentation Navigation System (MSAS – Japan), GPS-Aided GEO Augmented Navigation System (GAGAN – India) and the System for Differential Corrections and Monitoring (SDCM - Russia).

Other techniques to improve positioning accuracy include real-time kinematic (RTK), precise point positioning (PPP) and if real-time transmission is not required, GNSS data post-processing can result in a more accurate positioning solution (Hexagon Positioning

Intelligence, 2019). Working with these accuracy-boosting strategies, current GNSS monitoring boasts <10cm positioning accuracy (NASA, 2018).

With receiver quality playing a role in the accuracy of data collected, there will always be variation between systems. Due to the time taken to publish studies to test the validity and reliability of GNSS devices, they are often used in sport before essential independent information on measurement precision is available (Malone et al., 2017a).

*2.3.3 Validity and reliability of GNSS devices*

Validity is the ability of the measurement tool to reflect what it is designed to measure (Atkinson and Nevill, 1998). Reliability is the consistency of measurements, or of an individual's performance, on a test; or 'the absence of measurement error' (Safrit and Wood, 1989). For any testing results to be considered valid, the testing protocol and assessment tool used firstly needs to be considered valid and reliable through well-constructed study design (Atkinson and Nevill, 1998).

Studies are carried out on GNSS devices to measure athlete movement in order to separate the 'signal' from the 'noise' (error) to confidently make evidence-based decisions (Malone et al., 2019). As athlete monitoring should be conducted at an individual level to identify meaningful change, it is important to understand the accuracy and reliability of the devices used as this will allow practitioners to determine the athlete's day-to-day variation in these measures and confidently determine meaningful changes in load (Cardinale and Varley, 2018). Due to the time taken to publish studies to test the validity and reliability of GNSS devices, they are often used in sport before essential independent information on measurement precision is available (Malone et al., 2017a).

The FIFA Quality Programme for wearable EPTS devices was launched in 2017 with the aim of ensuring that wearable tracking systems used in football do not pose a danger to the players and ensure accuracy standards. In order to obtain the international match standard (IMS) and be listed as an approved wearable technology, each system must be tested by an accredited independent test institute (FIFA, 2019). A FIFA driven study explored the validity of 16 different Electronic Performance Tracking Systems (EPTS) (FIFA, 2018) and if the devices were deemed accurate and safe, they became a certified EPTS to measure output of soccer training and matches. The study provided a platform for manufacturers to have their devices tested and certified against a gold standard criterion measure. Testing dates can now be regularly accessed, ensuring devices can be certified before going to market, therefore holding providers accountable to industry-wide accuracy levels and allowing club practitioners to make informed decisions on technologies to invest in.

GNSS validation studies (inclusive of those just using GPS) cover a breadth of sports and show vast variation in experimental design dating back to the early 2000's (Aughey, 2011). Prevailing conclusions support the use of devices in team sport activities but recommend caution with measurement of rapid acceleration over short distances (Rawstorn et al., 2014). Decreased reliability during increased movement intensity is a common finding (Petersen et al., 2009; Coutts and Duffield, 2010; Gray et al., 2010; Jennings et al., 2010; Akenhead et al., 2013a). Establishing the degree of accuracy of modern GNSS devices to measure distance and speed during high-intensity, short-distance actions is vital for practitioners working with team sports. This is especially key in elite soccer as match play has been shown to elicit around 220 high speed runs (Mohr, Krustrup and Bangsbo, 2003), 178 ± 38 accelerations above 3 m-s$^2$ and 162 ± 29 decelerations above 3 m-s$^2$ (Akenhead et al., 2013a) with a change in activity every 4-6 seconds (Bangsbo, 1994).

Summarising the research, GNSS technology has been shown to be a valid and reliable tool to measure distance in team sports (Peterson et al., 2009; Coutts and Duffield, 2010; Varley et al., 2012; Beato et al., 2016; Beato et al., 2018). Data error increases when movement increases in complexity and change of direction (Portas et al., 2010; Rawstorn et al., 2014) and when the athlete is moving at high velocities (Grey et al., 2010). Additionally, accuracy is compromised during increased acceleration (Varley and Aughey, 2013; Akenhead et al., 2013a). Whilst GNSS devices have been shown to be valid to measure distance in team sports regardless of sample rate, higher sampling frequency devices (10- and 15-Hz) have been shown to be more accurate and reliable than 1- and 5-Hz units (Scott, Scott and Kelly, 2016). Recent studies have since shown that technological developments have elicited accuracy improvement at an even greater (18-Hz) sampling rate (Beato et al., 2018).

Practitioners should be mindful that whilst manufacturer-recommended upgrades in device firmware will improve certain operational aspects (e.g. bug fixes), they may also affect data output, and thus interpretations of longitudinal data (Varley et al. 2017). With ever-developing technologies, it is important to gain independent information on measurement precision.

Number of visible satellites and HDOP are two contributors to GNSS accuracy, since there is a moderate negative correlation between the distance error and these measures (Scott, Scott and Kelly, 2016). Practitioners are encouraged to ensure that they adhere to the recommended guidelines for data collection, processing and reporting (Malone et al., 2017a) and relevant information such as the number of satellites visualised (and horizontal dilution of precision, <1 is seen as ideal) is now provided in the latest devices (Beato et al, 2018).

Practitioners are encouraged to conduct their own in-house validity and reliability assessments on the specific device and metrics used (Malone et al., 2019); however, the FIFA certification and testing system gives practitioners confidence to monitor training and match load and accurately.

### *2.4 Monitoring load in elite soccer*

#### *2.4.1 Introduction*

The increased use of GNSS-enabled devices with inertial sensors has led to an increased access to data for applied practitioners to monitor training and match activity and investigate relationships between physical capacity and match performance (Aughey, 2011). This increase in available information is mirrored by exponential growth in research from 3 to 136 articles per year between 2001 and 2018 (PubMed) investigating these relationships (Malone et al., 2019) and a recent PubMed Search (July 2016) identified 488 papers with the keywords training load monitoring (Cardinale and Varley, 2018). Interest resides in the need to improve and individualise the design of training programmes to maximise the improvements in athletic performance and avoid overtraining or overreaching.

Metrics used to measure training load can be categorised as either internal (the relative biological stress incorporating both physiological and psychological) or external (objective measures of the work performed by the athlete during training or competition and assessed independently of internal workloads) (Bourdon et al., 2017). Metrics should relate to the training outcome that is of interest and ultimately linked to the sporting demands (Impellizzeri, Marcora and Coutts, 2019). Monitoring the training load of an athlete is important to determine whether an athlete is adapting to the training programme and to minimise the risk of non-functional overreaching (fatigue lasting weeks to months), injury, and illness (Halson, 2014). The concepts of internal and external training load were presented in 2003 (Impellizzeri, 2003) and featured in research, practice in the context of team sports (Impellizzeri, Marcora and Coutts, 2019).

To obtain specific performance adaptations, training of athletes needs to target the systems that determine performance, which will incorporate the relationship between the programmed external load and the subsequent internal load response (Figure 2.4) leading to adaptation (Impellizzeri et al., 2019).

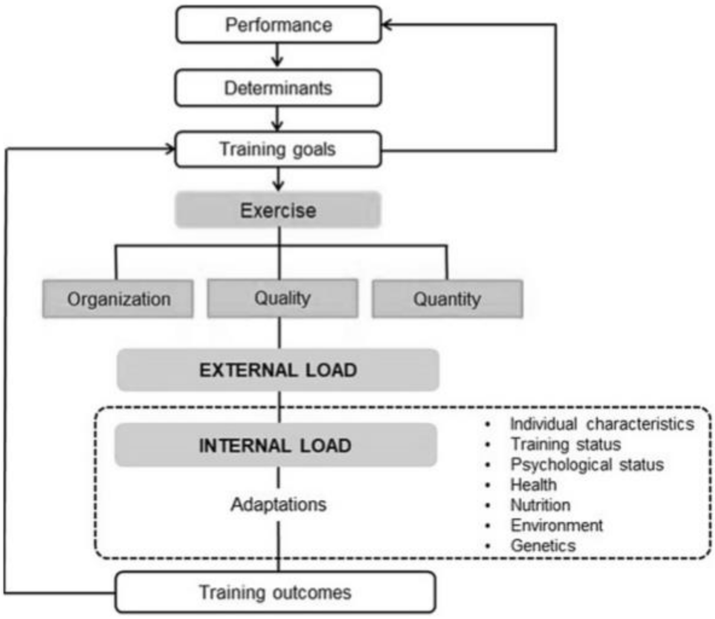



*Figure 2.4 Theoretical framework of the training process presented in 'Internal and External Training Load: 15 Years On' (Impellizzeri et al., 2019)*

### *2.4.2 The monitoring of soccer player load using external load metrics*

The organisation, quality, and quantity of exercise (training plan) determine the external load measures monitored to ensure they are specific to the nature of training undertaken (Impellizzeri et al., 2019). Common measures of external load are time, training frequency, distance (m), training mode, power output (W), and metrics which can be produced by GNSS devices such as speed (km $h^{-1}$), acceleration ($m/s^2$) along with subsequent aggregates derived from these metrics (Bourdon et al., 2017; Clemente et al., 2018; Newton et al., 2019). Technologies used to measure external load include the aforementioned integrated electronic performance tracking systems (GNSS devices, accelerometers, gyroscopes and magnetometers), power output measuring devices such as Power Tap and neuromuscular function measures such as jump mats (countermovement/squat jump), timing gates (sprint performance), and isokinetic and isoinertial technologies to measure muscular strength (Halson, 2014).

### *2.4.3 The monitoring of soccer player load using internal load metrics*

Irrespective of how it is quantified, coaches prescribe training according to external load to elicit the desired psychophysiological response. It is this response which corresponds to the internal training load (Impellizzeri et al., 2019). Common measures of internal load are rate of perceived exertion (RPE), training impulse (TRIMP – using heart rate to consider the intensity of exercise as calculated by the HR reserve method and the duration of exercise – Banister, 1991), heart rate indices, biological assessments (creatine kinase, blood lactate), wellness questionnaires and psychological inventories (Bourdon et al., 2017).

Where external load measures can be relatively easy and non-invasive to collect, a comprehensive quantification of internal training load is impractical due to the limitation of current technology and logistics. Holistic internal load assessment would require athletes to wear multiple, some intrusive, monitoring devices (Figure 2.5) whilst training (Cardinale and Varley, 2018).

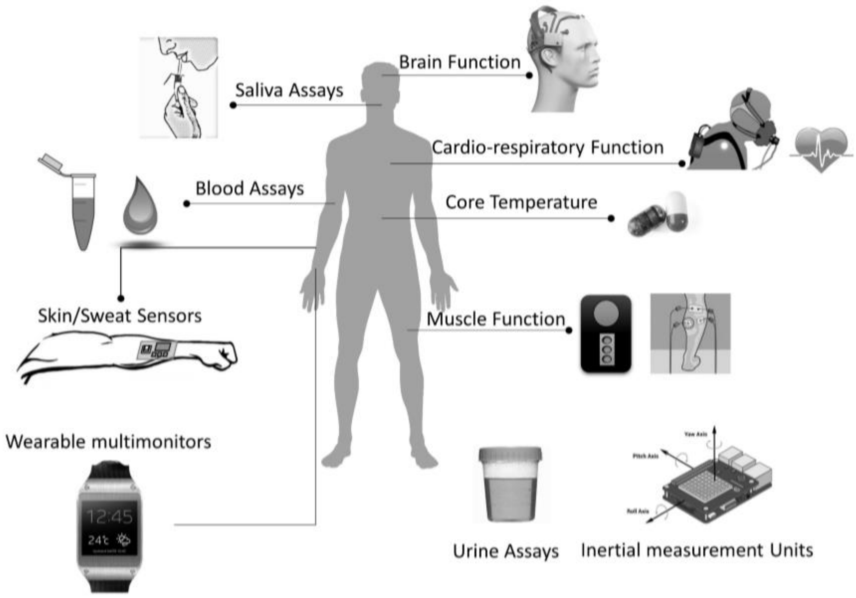



*Figure 2.5 Schematic diagram summarising technologies used to measure internal load from 'Wearable training-monitoring technology: Applications, challenges and opportunities' (Cardinale and Varley, 2018)*

It is noted that the internal training load determines the training outcome (impact of external load can vary depending on specific contextual factors and other stressors either between or within athletes – Vellers et al., 2018) and is therefore an important part of the monitoring process (Impellizzeri et al., 2019). These factors appear to be important moderators of the relationship training load has with performance and injury (Coyne et al., 2018).

### *2.4.4 Analysing training load data*

One of the major challenges for practitioners who analyse training data is to make meaningful inferences on the efficacy of the training processes for individual athletes and coaches (Bourdon et al., 2017). There is limited research exploring how key metrics should be selected, how such data should be analysed, aggregated, how meaningful information can be extracted and which methods present these data most effectively (Thornton et al., 2019). Given the large quantity of data available to performance practitioners, selection of which data best help to answer the questions of coaches and athletes is vital (Buchheit, 2017). There are several steps with various considerations to developing an effective data analysis process (Figure 2.6), with practitioners needing to be aware of factors such as collection logistics, data accuracy and reporting processes (Thornton et al., 2019).

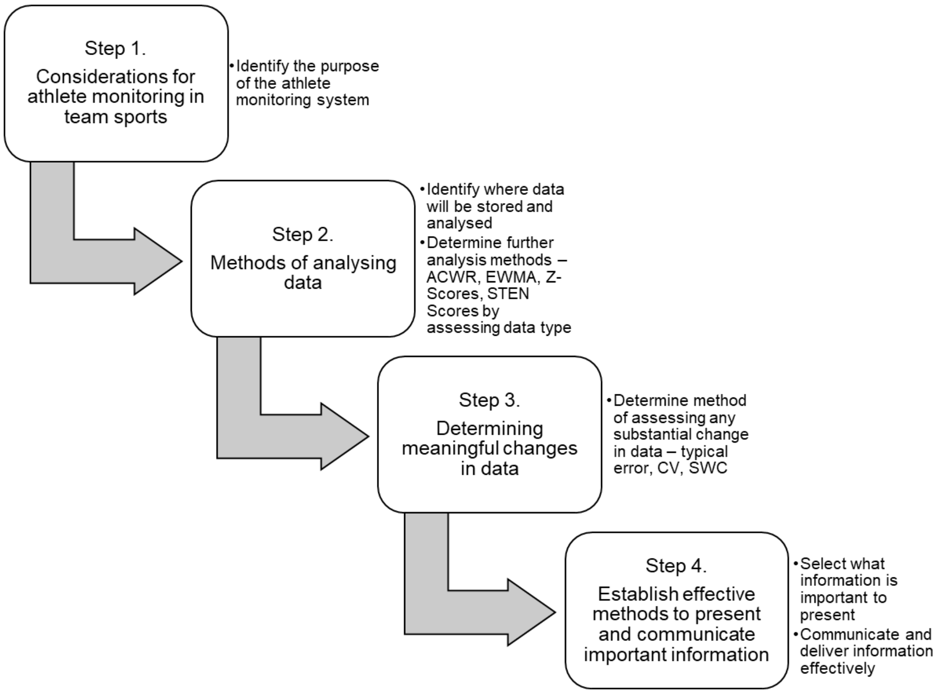



*Figure 2.6 Athlete Management System (AMS) development steps in team sports. ACWR indicates acute-to-chronic-workload ratio; EWMA, exponentially weighted moving averages; STEN, standard tens; SWC, smallest worthwhile change; CV. coefficient of variation; MBI, magnitude-based inferences from 'Developing Athlete Monitoring Systems in Team Sports: Data Analysis and Visualization Fitness fatigue model' (Thornton et al., 2019)*

A variety of analysis methods arise from computer-based support systems to provide objective evidence relating to the decision making of organisations (Robertson et al., 2017). The fitness-fatigue model is one which is used to analyse the response to fitness training. As outlined by Hellard et al., (2006), the below depicts an equation described by two antagonist transfer functions (fitness and fatigue). *pt* is the modelled performance at time *t; p0* is the initial performance level; *ka* and *kf* are the respective fitness and fatigue magnitude factor; *τa* and *τf* represent the decay time constants and *wt* is the known training load per week (or day) from the first week of training to the week (or day) preceding the performance. (Banister et al., 1975; Busso et al., 1994; Hellard et al., 2006):

$$Pt = P_0 + Ka\sum_{s=0}^{t-1} e^{-(t-s)/\tau_a} w_s - k_f \sum_{s=0}^{t-1} e^{-(t-s)/\tau_f} w_s$$

This model has been the cornerstone for subsequent models to analyse training load relationships and the evolution and refining steps are outlined by Hayes and Quinn (2009). Each model suggests that the training impulse (or training load) elicits fitness responses that increase performance and also produce fatigue responses that decrease performance (Bourdon et al., 2017). The popularity of this model is evident with researchers and practitioners using the principles to guide training planning and predict future performance. Critique of this method cite the oversimplification of the training-performance relationship (Hellard et al., 2006), particularly as it assumes a single measure to represent performance which in team sports, especially soccer, is limited due to the multifactorial nature of performance.

Using the principles of Banister's model, the acute-chronic workload ratio (ACWR) uses rolling averages to relate recent (acute) load with load over a longer period (chronic) (Hulin et al., 2016). Used to identify injury risk in different sports including rugby league (Hulin et al., 2016), Australian football (Murray et al., 2016) and soccer (Bowen et al., 2017), initial studies suggested injury risk increases as acute workload outweighs chronic workload and that the greater the increase in acute workload relative to chronic workload, the larger the increase in injury risk in the following week (Hulin *et al*., 2014, Hulin *et al*., 2016). A common emerging message is when the ACWR is within a 'sweet spot' of 0.8 – 1.3, risk of injury was relatively low and when the ratio increased (≥ 1.5), the risk of injury increased markedly (Hulin *et al*., 2014; Blanch and Gabbett, 2016; Murray *et al*., 2017b; Malone *et al*., 2017b).

Developments of the ACWR modelling method suggest different acute:chronic durations should be used to better fit the specificity of training/competitive patterns (Carey et al., 2017; Malone et al., 2018; Stares et al., 2018). The optimal duration of both the chronic (2 vs 3 vs 4 weeks, based on off-season and preseason durations) and acute (3 vs 7 days, based on matches occurrence) explores whether analysis is specific to soccer (Buchheit, 2017). Caution is still advised when using this ratio to predict injury; therefore, it is important to report as association rather than prediction (Franchini et al., 2018).

Further critique of these modelling methods includes the theory that rolling averages fail to account for the decaying nature of fitness and fatigue effects over time (Menaspà, 2017). The use of exponentially weighted moving averages (EWMA) is an alternative method, assigning a decreasing weighting to compensate for the latency effects of loads (Williams et al., 2016b). Other critical research highlighted evidence of spurious correlation as the numerator and denominator in the ACWR are mathematically coupled (Lolli et al., 2018). Additionally, using discrete metrics to model the continuous U-shaped risk profile between ACWR and injury can result in inflated false discovery and false rejection rates (Carey et al., 2018). This process of discretisation is the practice of transforming continuous data into discrete categories and is prevalent in studies of training load and injury risk. Critically examined in other fields (Altman and Royston, 2006; Bennette and Vickers, 2012), the practice has been recently critiqued with specific reference to modelling training load and injury (Carey et al., 2017) as it results in loss of information (Bennette and Vickers, 2012), reduces ability to detect metric relationships and increases likelihood of a false-negative result (Altman and Royston, 2006; Bennette and Vickers, 2012; Kahan et al., 2016). It was recently suggested that previously used discrete methods are unsuited to modelling the risk profile between ACWR and injury and the use of continuous modelling methods (spline regression and fractional polynomials) demonstrated by a lower root mean square error (RMSE) when analysing their relationship to injury (Carey et al., 2018).

Combining internal and external load aims to understand how athletes are coping with training and competition (Bourdon et al., 2017). Preliminary results using data from amateur soccer players suggest the use of these ratios present advancement from the use of external load alone in the assessment of aerobic fitness, and detection of ratio change may help in the assessment of fatigue (Akubat et al., 2014). Another method, assessing the relationship between training and match play can highlight discrepancies and guide coaches to programme training to bridge the gap or manage fatigue references through to match load (Clemente et al., 2019).

Training load is the input metric into a training system and as such, quantifying and analysis training load should be the corner-stone of athlete monitoring (Coutts et al., 2018). There has been an exponential increase in the quantity of athlete monitoring data collected within team sports and analytical methods can be used to investigate any meaningful change that has occurred (Thornton et al.,2019). It is important data can be communicated efficiently to allow informed decisions regarding athlete status to ultimately improve performance and reduce the risk of any adverse effect of sport training and match-play.

## *2.5 Epidemiology of injury in elite soccer*

### *2.5.1 Introduction*

Injury in sport can be defined and categorised in different ways; however, a consensus in soccer is:

*'Any physical complaint sustained by a player that results from a football match or football training, irrespective of the need for medical attention or time loss from football activities. An injury that results in a player receiving medical attention is referred to as a ''medical attention'' injury, and an injury that results in a player being unable to take a full part in future football training or match play as a ''time loss'' injury' (*Fuller *et al.*, 2006*).*

Most soccer studies use the 'time loss' definition for injury (Nielsen and Yde, 1989; Hawkins and Fuller, 1999; Junge, Chomiak and Dvorak, 2000; Hawkins et al., 2001; Árnason et al., 2004; Ekstrand et al., 2004). This definition is preferred over medical definitions as the latter can introduce observer and patient bias due to the subjectivity of examination and injury underestimation could occur if clubs don't employ full time medical personnel (Hägglund et al., 2005).

Classification of injury is important to classify diagnoses accurately for research or injury surveillance, maintaining diagnostic detail and also permitting easy grouping into parent classifications for summary and to create a database from which cases can be extracted for research on particular injuries (Rae and Orchard, 2007). The Orchard Sports Injury Classification System (OSICS) is one of the world's most commonly used systems (Hammond et al., 2009), developed in 1992, originally for assessing injury incidence at the elite level of Australian rules football, rugby league, and rugby union in Australia. The OSICS has now progressed to iteration 10.1 (Figure 2.7) and used across many sports due to being free from copyright, its universal availability of use and being specific to sports medicine allowing diagnoses to be easily classified and grouped therefore encouraging more generalised analysis of injury patterns (Rae and Orchard, 2007).

| OSICS10 code | Specific | Detail | OSICS9 |
|---|---|---|---|
| HXXX | Head injuries | Head injuries | |
| HHXX | Head/facial bruising/haematoma | Head/facial bruising/haematoma | HHI |
| HHOX | Eye bruising/haematoma | Eye bruising/haematoma | HHO |
| HHOO | Eye bruising/haematoma | Periorbital bruising/haematoma | |
| HHOC | Eye bruising/haematoma | Conjunctival haematoma | |
| HHSX | Scalp bruising/haematoma | Scalp bruising/haematoma | HHS |
| HHNX | Nose bruising/haematoma | Nose bruising/haematoma | HHN |
| HHNE | Nose bruising/haematoma | Epistaxis | HVI |
| HHNS | Nose bruising/haematoma | Septal haematoma | |
| HHMX | Mouth bruising/haematoma | Mouth bruising/haematoma | HHM |
| HHEX | Ear bruising/haematoma | Ear bruising/haematoma | HHE |
| HHEC | Ear bruising/haematoma | Cauliflower ear (chronic) | |
| HHJX | Jaw bruising/haematoma | Jaw bruising/haematoma | |
| HHZX | Other bruising/haematoma not | Other bruising/haematoma not | |

*Figure 2.7 Example codes to classify sports injury surveillance data from 'Has version 10 of the Orchard Sports Injury Classification System improved the classification of sports medicine diagnoses? (Hammond et al., 2009)*

Player availability is associated with team performance (Árnason et al., 2004; Eirale et al., 2013; Hägglund et al., 2013; Podlog et al., 2016; Raysmith and Drew, 2016). Injury or illness impacts team selection, path of match success and results in negative psychological effects for the injured player or whole squad (Hägglund et al., 2013). Injuries also affect sports teams financially due to rises in medical fees and insurance premiums (Gallo et al., 2006) and the effect on longer-term quality of life for the player (King et al., 2013).

An injury aetiology model (example in Figure 2.8) can show the potential risk pathway to injury (Windt and Gabbett, 2017). The workload-injury relationship relates workload, perceptual well-being and physical preparedness (Gabbett, 2018). It collaborates factors like age, injury history, training history, lower body strength, aerobic fitness and heart rate variability, therefore highlighting the multi-factorial nature of injury. Additionally, this model illustrates how biomechanical factors, academic and emotional stress, anxiety and sleep can influence training adaptation (Gabbett, 2018).

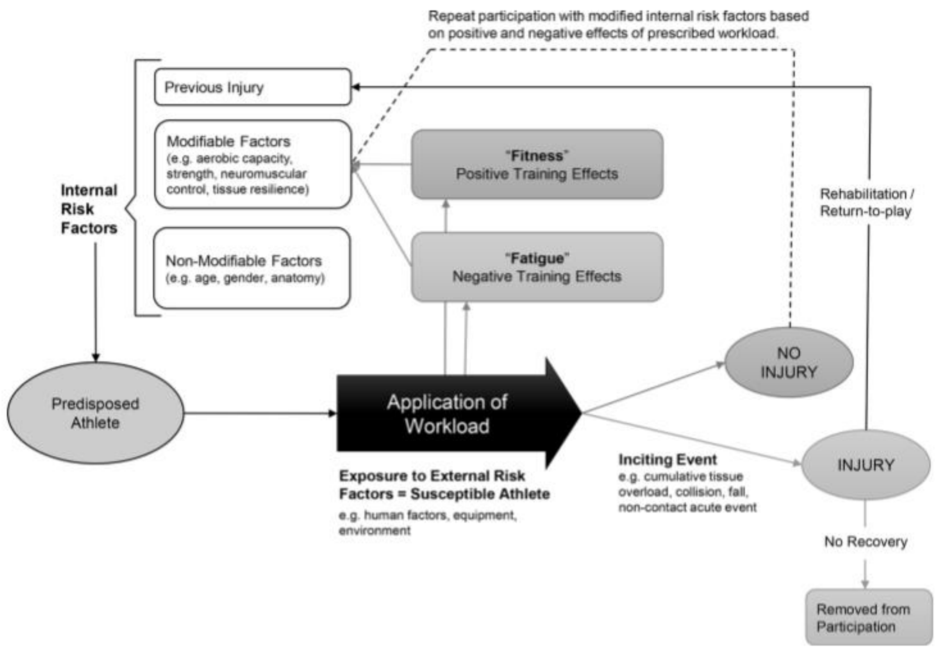



*Figure 2.8 The workload–injury aetiology model presented in 'How do training and competition workloads relate to injury? The workload— injury aetiology model' (Windt and Gabbett, 2017)*

Injury rates in soccer, expressed in various formats (most commonly number of injuries per 1000 hours), are known to be relatively high (between 3.4 and 5.9 per 1000 training hours and 25.9 and 34.8 per 1000 match hours) compared with participants in other sports and other occupations (Hawkins and Fuller, 1999; Arnason et al., 2004; Ekstrand, Waldén and Hägglund, 2004; Waldén, Hagglund and Ekstrand, 2005; Ekstrand, Hägglund and Waldén, 2011). Muscle injury is one of the major problems, often categorised as 'preventable injuries', representing 20% to 37% of all time-loss injuries at elite soccer clubs (Ekstrand, Hägglund and Waldén, 2011). Further categorisation of muscle injury demonstrates that 92% of all muscle injuries sustained by professional soccer players occur in one of four areas: hamstrings, adductors, quadriceps or calf, with the majority (37%) occurring in the hamstrings (Hawkins and Fuller, 1999; Arnason et al., 2004; Ekstrand et al., 2011). Multifactorial modelling (Figure

2.8), developed to help explain injury incidence (Meeuwisse, 1994; Windt and Gabbett, 2017) highlights that although certain external risk factors such as opponent behaviour cannot be accounted for, the importance of identifying the modifiable risk factors for injury will encourage the implementation of preventative strategies. A considerable proportion of injuries are as a result of excessive training loads, inadequate recovery and overtraining (Gabbett and Domrow, 2007; Gabbett, 2010) and the analysis of training load is critical to ensure that players receive a progressive training programme to maximise performance without unduly increasing injury incidence.

*2.5.2 Load monitoring and injury*

The association between training load, defined as the cumulative amount of stress placed on an individual from single or multiple training sessions over a period (Soligard et al., 2016; Eckard et al., 2018) and injury incidence is an area of increasing research activity due to rising levels of competition and the impact of player availability on success (Drew et al., 2017). An important modifiable risk factor and a part of the injury occurrence pathway (Figure 2.8), research has recently collated and evaluated several training load and injury relationship review articles (Drew and Finch, 2016; Jones et al., 2017; Jaspers et al., 2017; Eckard et al., 2018, Gabbett, 2018).

It is well established that measuring and managing training loads should be part of an injury prevention programme (Drew and Finch, 2016). A recent review highlighting a ‘PubMed’ search of keywords ‘training load’ and ‘injury’ shows that in the past 18 years, there has been a rapid growth (Figure 2.9) in published articles (Gabbett, 2018).

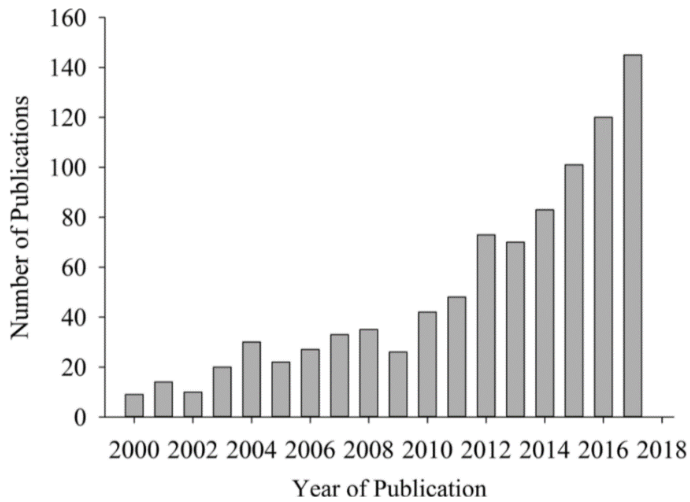



*Figure 2.9 Growth in research including the keywords ‘training’ and ‘injury’ since 2000 from 'Debunking the myths about training load, injury and performance: empirical evidence, hot topics and recommendations for practitioner’ (Gabbett, 2018)*

Early reviews show there was ‘emerging moderate evidence’ for a relationship between training load and injury risk (Jones et al., 2017; Drew et al., 2017). More recently the evidence for the existence of this relationship has shifted from emerging to established at a ‘moderate’ level (Eckard et al., 2018). It was noted that randomised control trials (RCTs) will allow for the relationship strength to be further established (Van Tulder et al., 2003).

Assessing internal, external, absolute and relative load measures in basketball (Weiss et al., 2017), rugby (Williams et al., 2016a), and soccer (Malone et al., 2018), it is suggested that low load may not be enough to elicit protective physiological adaptations in athletes, while high loads may result in overloading of tissue or decreased injury resistance by some other mechanism. Gabbett’s ‘training load–injury paradox’ states that athletes accustomed to high chronic loads have fewer injuries than those accustomed to lower loads, supporting the assertion that higher chronic loads can act as a protective ‘vaccine’ against future injury (Gabbett, 2016).

There are a number of misconceptions about the evidence supporting training load, its role in injury incidence and the actual training programmes prescribed (Gabbett, 2018). Load cannot explain all injuries and it is important to highlight the multifactorial determinants of injury, pertinently, the two strongest risk factors being age and injury history (Arneson et al., 2004; Hagglund et al., 2007; Ekstrand et al., 2011). Rapid change in training load increases the risk of injury (Gabbett, 2016); however, caution is recommended when using guidelines to implement load progression to make sure load increase is not necessarily delayed (Gabbett, 2018). The previously discussed ACWR has highlighted across many sports that rapid increases in workload have been associated with increased injury risk (Hulin et al., 2014; Erhmann et al., 2016; Murrey et al., 2017; Carey et al., 2017; Bowen et al., 2017; Cross et al., 2017; Stares et al., 2018; Malone et al., 2018). However, due to the multifactorial nature of injury, just because an athlete is at risk due to load increase, injury may not occur and often it is necessary to elicit greater physiological adaptations through big increases in load for enhanced performance (Gabbett, 2018). The protective effect of training appears to arise from exposure, allowing the body to tolerate load and subsequently develop specific physical qualities like strength, prolonged high-intensity running ability and aerobic fitness (Malone et al., 2017b; Gabbett et al., 2012; Gabbett, 2018). It is key for sport science practitioners to understand that physically hard training is required to prepare athletes for the demands of competition, but also to be aware that excessive loading can result in increased injury risk (Bourdon et al., 2017).

With the rate of development in technology and wearable analytic tools, practitioners have access to more solutions for analysing load, which brings the aforementioned challenges of validity and reliability and raises significant issues around the interpretation of data (Bourdon et al., 2017). Studies that evaluate the ability of training load monitoring to predict future injury are not currently well established (Carey et al., 2018). The ability to 'predict' outcomes such as performance, talent, or injury is arguably sports science and medicine's modern-day equivalent of the 'Quest for the Holy Grail' (McCall, Fanchini and Coutts, 2017).

### *2.5.3 Injury prediction*

Early injury prediction research utilising screening tests conclude that injury prediction with sufficient accuracy is unlikely (Bahr, 2016). The prediction debate can be linked to terminology used (Figure 2.10) by authors, often resulting in a mismatch between statistical modelling and subsequent interpretation of findings (i.e. analysing association and interpreting this as prediction) (McCall, Fanchini and Coutts, 2017). This misinterpretation is created by an absence of a clear definition of terms and a lack of understanding of the difference between association, explanatory power and predictive power (Shmueli, 2011). Within elite sport, due to the potential impact of the advice provided, care must be taken to ensure that our own understanding of the information being provided is correct. Misinterpretation of the use of load metrics to predict injury occurrence may result in a misclassification of players (indicating that a player will incur an injury and he or she does not) (Soligard et al., 2016) and a loss of practitioner 'credibility' to advise based on prediction data and the indicator itself (McCall et al., 2017).

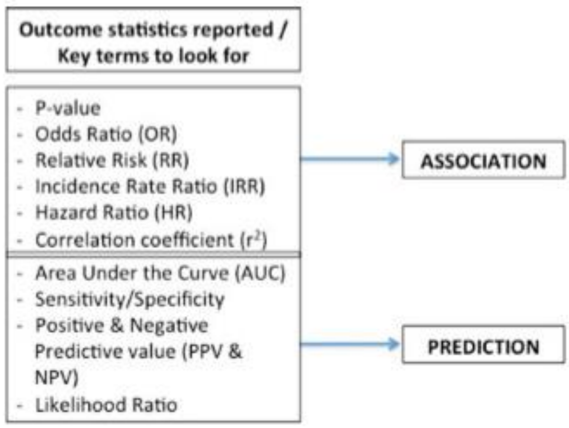



*Figure 2.10 Common statistical terms used to distinguish between associations and prediction from 'Prediction: The Modern-Day Sport-Science and Sports-Medicine 'Quest for the Holy Grail'* (*McCall, Fanchini and Coutts, 2017*)

Explanatory power (association) and predictive power have different interpretation qualities, and prediction of musculoskeletal injury risk is an area of increasing research activity due to the impact of player availability on success in elite sports organisations (Soligard et al., 2016; Drew et al., 2017; Eckard et al., 2018). A pertinent study investigating predictive modelling of training loads and injury in Australian football used relative and absolute training loads, player ages and session types as predictors to run univariate and multivariate predictive models (logistical regression, random forest, general estimating equations and support vector machines) on two years of player monitoring data and then on one year of unseen future data (Carey et al., 2017). Models were compared using the area under the receiver operator characteristic (AUC). A perfect model would have an AUC of 1.0 and random guessing an AUC = 0.5. Univariate models performed worse than multivariate models for each injury outcome and the best performing multivariate model used regularised linear regression to model hamstring injuries (mean AUC 0.72). In general, models provided predictions only marginally better than chance (Carey et al., 2017) and similar results were found in a study in rugby league (AUC 0.64 - 0.74). Implementing such a model in practice would require practitioners to consider how much modification of player training they are willing to accept in an attempt to prevent injuries (false positive rate).

Similar results were found in soccer with the predictive model performance not significantly better than random classifiers (Kampakis, 2016). More recently however, a study used a multi-dimensional approach that considered injury prediction as the problem of forecasting that a player will get injured in the next training session or official match, given their recent training workload (Rossi et al., 2018). The use of decision tree modelling detected approximately 80% of the injuries at 50% precision. This, coupled with a small false positive rate, is better than the baseline and injury risk estimation techniques (Rossi et al., 2018). The study states the usage of forecasting models allows for the prevention of more than half of the injuries in a soccer season once an initial period of data collection has commenced. Conclusions from this study are certainly positive to reaching the ‘holy grail’ of injury prediction however it is only based on data from one team, would benefit from multiple seasons and a deep understanding of machine learning techniques is required to implement models to elicit decision-making outcomes.

## ***2.6 Measuring performance in elite soccer***

### *2.6.1 Introduction*

Soccer is the most popular sport world-wide, but at the same time it is one of the least quantified in analysis of performance and the measurement of player contribution to success (Pelechrinis and Winston, 2019). The task of objectively quantifying the impact of the actions performed by individual players during matches, used in a variety of tasks within a soccer club, such as player acquisition, player evaluation, fan engagement, media reporting and scouting, remains largely unexplored (Decroos et al., 2019). Soccer analytics is lacking a comprehensive approach to address performance-related questions due to the low-scoring and dynamic nature of the sport (Fernandez et al., 2019). It is suggested that analysis methods that incorporate several facets of soccer, within a dynamic context, would appear to be superior and most appropriate to use (Ali, 2011). Selecting valid performance metrics, especially on an individual player level, provides a significant challenge to researchers and practitioners alike and much of the current research measure match performance in other team-sports. The measurement of performance can support the identification of talent, strategies for acquisition training interventions (Ali, 2011) and also opposition analysis to improve match preparedness.

### *2.6.2 Metrics to measure performance*

Current performance metrics used can be characterised as subjective (Cormack et al., 2008; Mooney et al., 2013; Rowell et al., 2018) and objective (Mooney et al., 2011; Sullivan et al., 2014; Lazarus et al., 2017; Graham et al., 2018; Egidi and Gabry, 2018; Pelechrinis and Winston, 2019; Decroos et al., 2019; Fernandez et al., 2019). The predominant subjective metrics utilised are variations of a coach rating scale, used in Australian Rules football (Cormack et al., 2008; Mooney et al., 2013) and soccer (Rowell et al., 2018). Use of these metrics assumes a scale along with consistency of feedback timing and personnel to ensure representative data. A Likert scale (1 = poor through to 5 = excellent) is a common scale used (Cormack et al., 2008; McLean et al., 2010; Rowell et al., 2018; Samuel et al., 2018).

External load metrics can easily focus on isolated aspects of the sport (Fernandez et al., 2019), for example in soccer, common metrics include tracking successful passes, shots, defensive duels and ball carries (Sarmento et al., 2014). These can be used in isolation to assess player performance but quantifying the impact of the individual actions performed remains largely unexplored (Decroos et al., 2019)

An integrated approach recently presented (Figure 2.11) contextualises match demands by assimilating physical and tactical data effectively (Bradley and Ade, 2018) and opens up the theory to use an integrated approach to assess team performance and the impact of individual performance on team success.

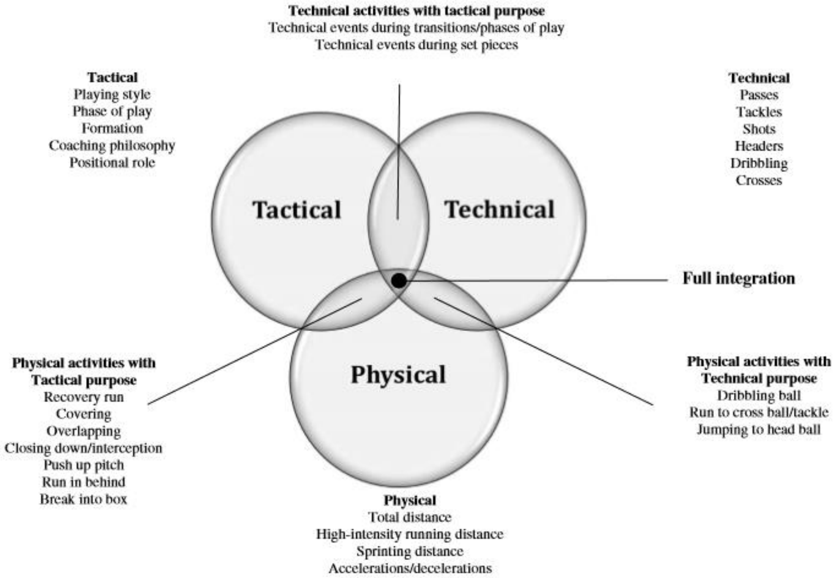



*Figure 2.11 Venn diagram depicting a generalised integrated approach to quantifying and interpreting the physical match performance of soccer players from 'Are Current Physical Match Performance Metrics in Elite Soccer Fit for Purpose or Is the Adoption of an Integrated Approach Needed' (Bradley and Ade, 2018)*

The concept of metric integration is adopted by analytics organisations that provide performance feedback to clubs and media. These platforms quickly and accurately provide a large range of match performance data, allowing the simultaneous analysis of the physical eff orts, movement patterns, and technical actions of players (Dellal et al., 2011). Champion Data provide the official statistics to the Australian Football League (AFL) and have created the player ranking system which assesses the impact of the players (Mooney et al., 2011) based on effective and ineffective skill execution throughout a match (Sullivan et al., 2014). In soccer, a similar data platform (InStat), presents a unique algorithm to provide an accurate assessment of a player's performance (InStat Index), recently used to analyse the association between running and match performance (Modric et al., 2019). This automatic algorithm considers the contribution of the player to team success the significance of their actions, opponent level and the level of the championship they play in (InStat, 2019).

### *2.6.3 The association between physical metrics and performance*

The ultimate goal of any sports coach and athlete is to produce optimal performance at a specific time with the role of scientific research becoming more important in order to prescribe optimal training programmes that prevent both under- and overtraining and increase the chance of achieving desired performances (Borensen and Lambert, 2009). The 'holy grail' for coaches and performance practitioners is to use information gathered through various metrics to predict and therefore effect subsequent performance. Match performance and physical performance metrics are often investigated separately; however, recent studies investigate them synonymously to identify possible associations which might exist between different parameters of players' conditioning status and indicators of real match performance (Modric et al., 2019). The use of linear mixed modelling of load and fitness data can assist in reducing injury and illness, subsequently increasing player availability for training programming; however, it does not necessarily facilitate enhanced football performance. Due to the complex nature of training, quadratic modelling appears valuable when examining the training-performance relationship (Lazarus et al., 2017), highlighting that performance staff should avoid prescribing substantially high weekly and sustained increases in load during the competitive period in AFL. A study in Australian soccer shows that the impact of training load on performance in A-League players appears to be position specific (Rowell et al., 2018), also a finding from the AFL study group (Lazarus et al., 2017).

Variable dose-response models can retrospectively predict performance in AFL matches (Player Ranking) using both external and internal quantitative input (Graham et al., 2018). It was commented future research should aim to cross-validate application of variable dose-response models in other high-performance team sports - this is yet to be established in soccer.

Elite soccer clubs continually strive for success and seek ways to optimise preparedness, covering every facet of what is a complex and demanding sport. Coaches, technical analysts, physiologists, sports scientists, conditioning specialists and medical practitioners such as doctors and physiotherapists make up extensive and expanding teams that are employed to support player performance and wellbeing. In recent years the influx in available data from new technology, pertinently to this thesis utilising the GNSS, has allowed sports science practitioners and data analysts to provide clubs with training and match output data at relative ease. This thesis aims to bring together this current body of research and subsequently contribute to further knowledge in this field to guide both research and applied practitioners, specifically focussing on the outlined thesis aims.

# CHAPTER 3: THE VALIDITY OF GLOBAL POSITIONING SYSTEM (GPS) DEVICES FOR MEASURING DISTANCE OF TEAM-SPORT SPECIFIC MOVEMENT

### *3.1 Chapter summary*

Elite soccer clubs across the world now have relative ease of access to GNSS devices to monitor training and match load. This study, commenced in 2014, assesses the criterion validity, of the (then) current GPS-enabled devices used by elite soccer clubs (STATSports, GPSports and Catapult). Criterion validity was established using an optoelectronic motion capture system (Qualisys), calibrated to 2.6mm in an outside space large enough to replicate soccer specific movement. Methods from this study are now utilised in the FIFA EPTS testing protocol allowing manufacturers the opportunity to certify device accuracy specifically the used of motion capture system as the criterion measure. The main findings of the study were that all three GPS devices reported moderate to large bias, generally overestimating distance and showed a weak linear relationship relative to a gold-standard measure. This was especially evident measuring actions with an increased change of direction, illustrating the limitations of this technology. The study corroborates with previous research that even with this knowledge of specific areas of inaccuracy, GPS devices are useful tools to measure team-sport specific movement and can therefore aid practitioners to guide the training process. The devices tested were used to investigate dimensionality reduction as a method to simplify training analysis (Chapter 4), provided insight into the statistical analysis used in elite teams and to analyse the influence of training load on the risk of injury (Chapter 5). During this study, new hardware utilising GNSS (certified by FIFA) was available and introduced (STATSports, Apex). The study documented through Chapter 3 used technology which presented challenges with both hardware and software. From planning, set up, data processing, data analysis through to documentation, it posed many challenges to be resolved with new skills learnt.

### *3.2 Introduction*

The global navigation satellite system (GNSS) is a general term that encompasses all global satellite-based positioning systems including GPS, GLONASS, Galileo, and BeiDou (Zimbelman and Keefe, 2017). Commercially available navigational technology is commonly used with team sports to measure the movement demands of training and match-play (Waldron et al., 2011; Wehbe et al., 2012; McLellan et al., 2013). With the advancement of technology, access to objective data to understand player movement output over a given training session have advanced (Beato et al., 2018). It is commonly agreed GNSS device data provides greater practicality and time efficiency compared with other monitoring technologies, for example video analysis (Carling et al., 2008; Petersen et al., 2009). It is well documented however, that devices utilising GNSS positioning have technological and practical limitations most notably the accuracy of the data collected, particularly with increased movement complexity (Scott, Scott and Kelly, 2016).

Accuracy of position data is determined by the precision of each satellite used for calculation, the accuracy of pseudorange measurements and actual satellite geometry (Januszewski, 2017). The user position error is a function of both the pseudorange error called UERE (User Equivalent Range Error), often called the signal in space (SIS) error and user-satellite geometry expressed by the dilution of precision (DOP) coefficient (Misra and Enge, 2006). The average SIS error for the GPS constellation was 0.9m in 2011 and the GLONASS SIS error was 1.6m in 2012 (Groves, 2013). Other factors contributing to error include atomic clock error, ephemeris error (cause by gravitational pull on satellites), weather conditions, local topography, foliage and building structures interfering with satellite signals (Shaw, 2004; Misra and Enge, 2006; Groves, 2013). A comprehensive explanation of the evolution and accuracy of satellite technology is described in Chapter 2.

Practitioners working with team-sports increasingly seek to investigate data, aiming to optimise the training environment and gain a competitive advantage over rivals (Buchheit et al., 2014b). The main applications of GNSS devices in team sports are collection and analysis of physical output metrics including total distance, high-speed running and accelerations (Varley, Gabbett and Aughey, 2013; Varley and Aughey, 2013; Varley, Gabbett and Aughey, 2014; Clark, 2014; Hodgson, Akenhead and Thomas, 2014). The information gained allows for greater analysis and planning of periodised external training load. The addition of match data provides an understanding of the specific movement demands, allowing the tailoring of match-specific training programmes (Scott, Scott and Kelly, 2016). The approved use of GNSS devices in official matches by FIFA, has accelerated research and development on position-tracking technology use (Pettersen et al., 2018).

Since the first evaluation of a GPS-enabled device in 1997 (Schutz and Chambaz, 1997), a large number of GPS/GNSS devices have been assessed for accuracy across different sport-specific trials (MacLeod et al., 2009; Petersen et al., 2009; Duffield et al., 2010; Gray et al., 2010; Jennings et al., 2010; Castellano et al., 2011; Waldron et al., 2011; Varley et al., 2012; Johnston et al., 2014; Rawston et al., 2014; Vickery et al., 2014; Beato et al., 2016; Beato et al., 2018). Devices have been shown to accurately quantify distances during team sport simulations and therefore their use during team sports matches and training that simulate match play movements can be justified (Scott, Scott and Kelly, 2016). GNSS devices are under continuous development and it is important that new devices are externally validated prior to being released to the market (Pettersen et al., 2018).

Percentage bias is a common statistical method of assessing criterion validity of GNSS device data against a known measure. A 5-Hz GNSS device produced good (3.7 ± 0.6%) accuracy when measuring distance of a team sport-specific circuit (Jennings et al., 2010). Testing shorter distances, 10-Hz GNSS devices produced moderate (6.5 ± 3.9%) accuracy for a 30 m trial protocol (Castallano et al., 2011). It is useful for practitioners to understand the accuracy and limitations of the technology they are utilising and how it affects their analysis in real terms. The real-terms error of a GPS enabled unit measuring a full soccer match (10881 ± 885 m) (Barnes et al., 2014), shown to be 3.17% (Rawstorn et al., 2014), equating to 340 – 380 m.

Validation studies have exposed GNSS devices to show poor accuracy when measuring high intensity running, high velocity measures, increased acceleration, short linear running and increases in changes of direction (Grey et al., 2010; Portas et al., 2010; Varley et al., 2011; Akenhead et al., 2013a; Rawstorn, et al., 2014). A study using VICON, a video motion capture analysis system, as a criterion measure highlights how accuracy decreases as speed increases. The co-efficient of variation (CV) was 3.6% for slower (2.6 ± 0.1 m/s) movement speeds, up to 7.6% for faster (4.9 ± 0.2 m/s) movement speeds (Duffield et al., 2010). Compared to the VICON system, GNSS devices underestimated the distance covered when speed and movement complexity increased.

The number of satellites to which devices can connect at the time of data collection will affect position estimation and therefore movement data accuracy (Witte and Wilson, 2004; Johnson and Barton, 2004; Grey et al., 2010). Device connection to four satellites is the theoretical minimum number needed to triangulate a GNSS receiver's position (Scott, Scott and Kelly, 2016), although there is a moderate negative correlation between the total distance error (i.e., the difference between the recorded distance and the actual distance) recorded by a GPS receiver and the number of satellites signalling the receiver (Grey et al., 2010).

The sampling frequency of GNSS devices is the rate at which the position is measured per second ranging from early devices sampling at 1-Hz (MacLeod et al., 2009). Recent devices have utilised a sampling rate of 18-Hz, improving the accuracy of data collection (Beato et al., 2018). Higher sampling frequency devices (10- and 15-Hz) have been shown to be more accurate and reliable than 1- and 5-Hz units (Scott, Scott and Kelly, 2016). One study shows device accuracy increases up until 10-Hz, but the rise to 15-Hz provided no additional benefit (Johnston et al., 2014). Further study considering satellite availability and mitigation of ionosphere error showed improved bias (3.5 ± 3.3%) from 10-Hz devices (Beato et al., 2016) to 18-Hz Units (1.15 ± 1.23%), supporting the sampling rate rise in new devices (Beato et al., 2018).

There are no standardised recommendations for the acceptable error for validity measures in this field but other studies have adopted measures of validity bias to be rated as good (<5%), moderate (5–10%), or poor (>10%) and advised that the gold standard criterion measure to be a motion capture system (Scott, Scott and Kelly, 2016).

For comprehensive criterion validity testing of GNSS device ability to measure sport-specific movement it is important to use a precise criterion measure. Examples used to measure distance, velocity or acceleration are laser systems (Siegle et al., 2013; Rampinini et al., 2015), timing gates (MacLeod et al., 2009; Frencken et al., 2013; Buchheit et al., 2014a) and motion capture systems (Duffield et al., 2010; Stevens et al., 2014; Vickery et al., 2014). Using a pre-marked path measured by a trundle wheel identified error in path taken by trial subjects adding to the total error, thus not fully representing device accuracy (Portas et al., 2010, Coutts and Duffield, 2010). Therefore, the use of an accurate criterion measure will highlight more closely the true accuracy of the measured device (Duffield et al., 2010).

Video camera motion capture systems for example, Qualisys (Qualisys, Gothenburg, Sweden) and Vicon (Oxford Metrics, UK), have been shown to be highly accurate measures of movement. A study using eight-Vicon T40S cameras measuring static experiments showed a mean absolute error of 0.15 mm, variability lower than 0.025 mm and dynamic movement error was less than 2 mm (Merriaux et al., 2017).

Data collection for this study was completed in 2014 on GPS-enabled devices that are still used by sports teams globally. The availability of newer systems to the market have provided better value and affordability of these models therefore wider use in a range or sporting environments. The movements considered in this study reflect a soccer physical profile - characterised by brief bouts of high-intensity linear and multidirectional activity (Varley et al., 2016), movements that have previously been shown to be measured inaccurately (Grey et al., 2010; Portas et al., 2010; Varley et al., 2011; Akenhead et al., 2013a; Rawstorn, et al., 2014). This study therefore addressed these movements within the trial protocols.

This study aims to use a video camera motion capture system to assess the validity of 10- and 15-Hz GPS-enabled devices to measure the distance of team-sport specific movement.

### *3.3 Methods*

#### *3.3.1 Participants*

One amateur male soccer player (26.3 years, 73.2 kg, 179.2 cm) volunteered to participate in this study. The experimental protocol was in accordance with the University of Bath department for Health Research Ethics Approval Committee. A written informed consent was obtained from the participant of this study.

#### *3.3.2 Technologies used*

Devices from three GPS device manufacturers were used: one non-differential 10-Hz Catapult Minimax device (MinimaX S4, 10-Hz, Firmware 6.70, Catapult Innovations, Melbourne, Australia), one non-differential 15-Hz GPSports devices (SPI-ProX, 15-Hz, Firmware V2. 4.3, GPSports, Canberra, Australia) and four non-differential 10-Hz STATSports devices (Viper, 10-Hz, STATSports, Newry, Ireland). Devices were worn in a custom-made vest accommodating three devices side by side between the participant’s scapulae (Figure 3.1), as per manufacturer recommendation.

Criterion validity was assessed using Qualisys (Qualisys, Gothenburg, Sweden), an optoelectronic motion capture system configured in an outside space (Figure 3.2), with twelve motion analysis cameras and one video camera (capture area of 15x3 m). The calibration process ensured an accuracy of 2.6 mm, which is in line with other kinematic studies (Merriaux *et al*., 2017). Twenty-one anatomical and technical markers were placed on the participant (Figure 3.3) including the device vest structure. An automatic identification of markers model (AIM) was created and applied to each trial marker trajectories to label the twenty-one trajectories (Qualisys Track Manager, Qualisys, Sweden). Three marker trajectories (i.e. GPS, SHR and SHL) were chosen for analysis, as highlighted in Figure 3.3.

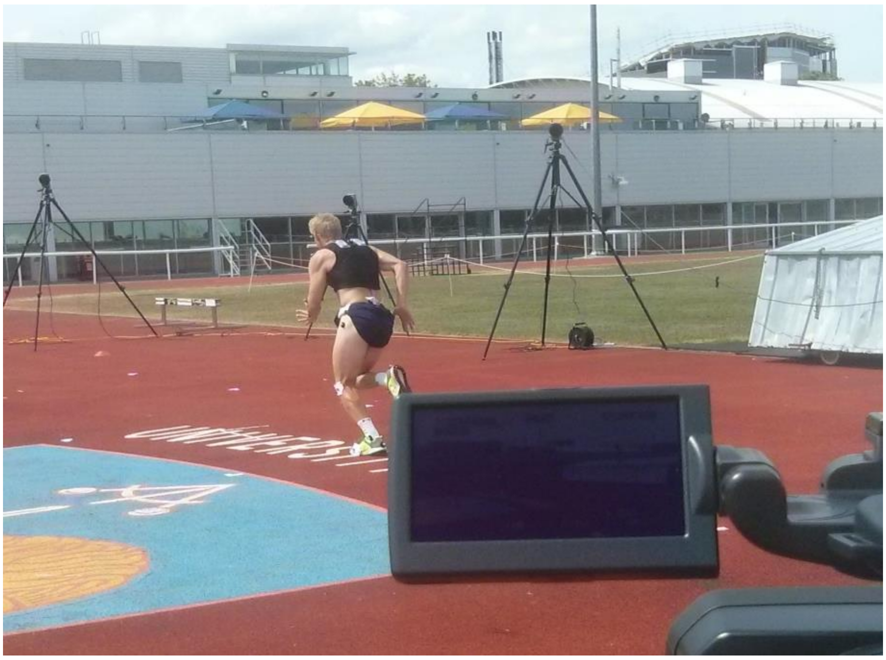


*Figure 3.1 Experimental set-up and device configuration in custom made vest during an acceleration trial*

*Figure 3.2 Motion capture system (Qualisys) set up configuration with 12 motion analysis cameras and one video camera. Calibrated to 2.6mm error over a capture area of 15x3m*

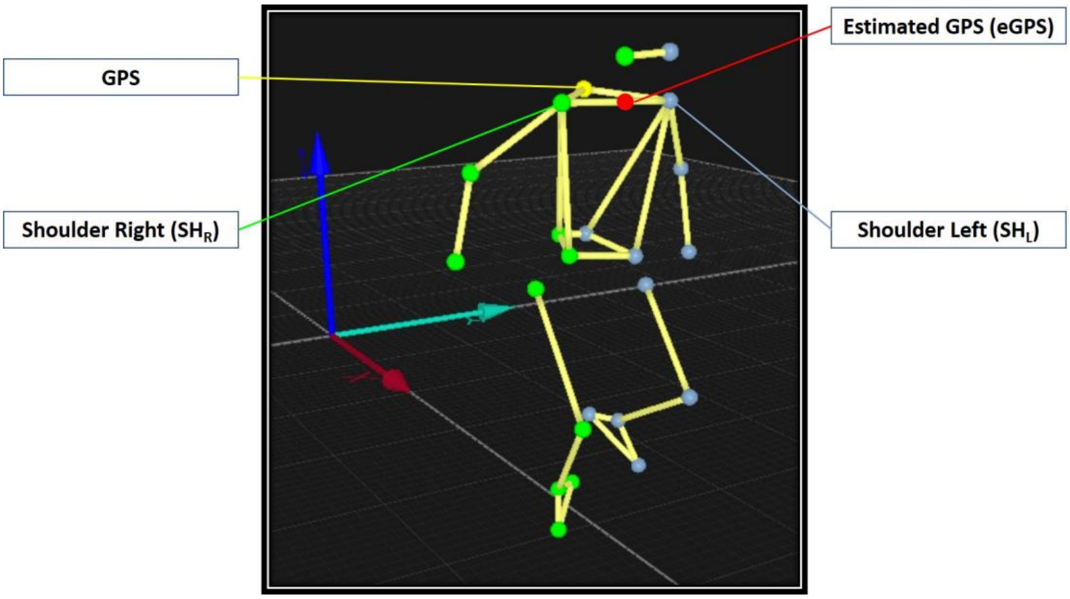



*Figure 3.3 Motion capture system (Qualisys) identification of marker model highlighting the marker labels used in the analysis.*

### *3.3.3 Experimental procedures*

After refraining from physical activity for the 48 hours prior, the participant completed two experimental trials of identical protocol: i) ten linear accelerations (A-B = 13.95 m), ii) ten change-of-direction shuttle runs (A-B-A-B = 41.85 m) and iii) ten multi-direction shuffle runs (A-B-C-D-E-F = 12.5 m). Representative schematics of each run are shown in Figure 3.4.

The first trial tested three STATSports Viper-2 devices and the second trial tested one device from each manufacturer. The participant had a ninety-minute break of complete rest between trials. To facilitate satellite connection, before each trial, the devices were switched on and left stationary for 15 minutes and then walked around a 400-m athletics track.

Weather conditions recorded at the time of the two trial periods were clear skies and sun with temperatures of 24ºC and 26ºC respectively. Number of satellite and horizontal dilution of precision (HDOP) data were missing due to STATSports system version (Beato et al., 2018).

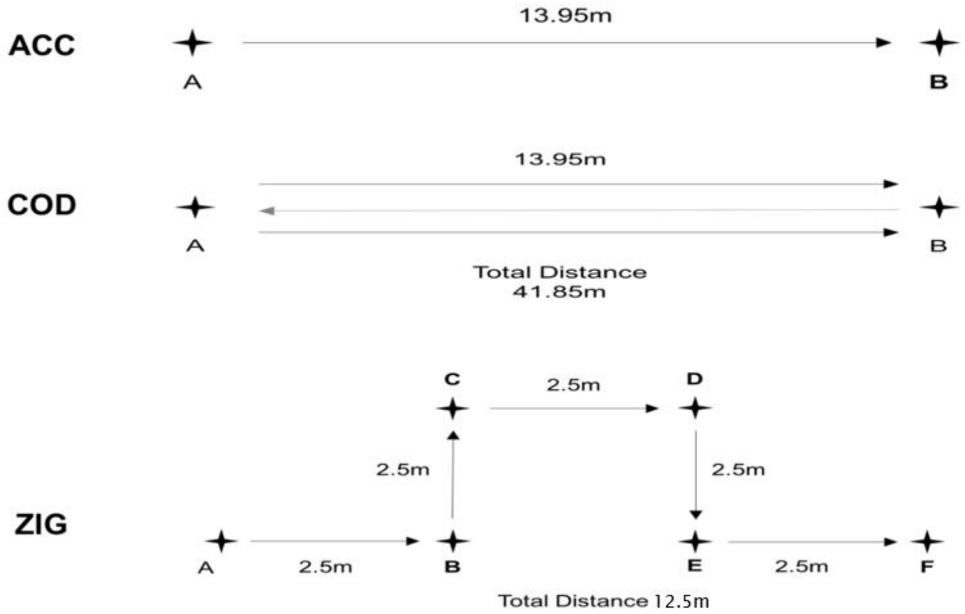



*Figure 3.4 Schematic of validity trial protocols; Acceleration (ACC) – subject runs from A-B with nil change of direction, Change of direction (COD) – Subject runs three consecutive shuttles between A-B-A-B finishing at B including two $180^0$ direction changes, Zig-Zag (ZIG) – Subject follows multi-direction change track alternating between forward running and linear shuffle movements*

System synchronisation was achieved by instructing the participant to stand in the stationary anatomical position at the start and end of each trial in order to 'standardise' the start and end position. A time stamp was recorded and stored to synchronise Qualisys and GPS data sets. Trials were completed in surroundings free from potential signal disruption i.e. buildings, extreme topography or high-level foliage.

Raw GPS data was downloaded using the respective manufacture software: STATSports (Viper 2.6.1.125), Catapult Logan Plus (v4.5) and GPSports Team AMS (v2.1). Qualisys raw files were processed using Qualisys Track manager (v2.10). The AIM model (Figure 3.3) was applied to each run to detect the twenty-one motion tags followed by manual processing of misidentified tags for three acknowledged tags (GPS, $SH_R$ and $SH_L$).

*3.3.4 Qualisys data processing*

To obtain the distance covered from each trial from the Qualisys data, a tiered process was used to calculate displacement after a clean-up of fragmented or deletion of poor data. Firstly, following the application of the AIM model, if the GPS marker was complete across the whole trial (48.3% of all trials), measured distance was calculated as follows:

The instantaneous displacement for the x (anterior-posterior) and y (medio-lateral) axis was calculated in metres (m) as following:

$dGPS_{x2} = GPS_{x2} + |GPS_{x2} - GPS_{x1}|$ *Equation 1*

$dGPS_{y2} = GPS_{y2} + |GPS_{y2} - GPS_{y1}|$ *Equation 2*

The displacement of GPS marker (dGPS) from frame to frame was calculated as following:

$dGPS = \sqrt{dGPS_x{}^2 + dGPS_y{}^2}$ *Equation 3*

In cases of complete GPS marker data, the final frame to frame calculation is the GPS marker total distance from initial to final position. In cases of incomplete GPS marker data (31.6% of trials), shoulder tags ($SH_L$ and $SH_R$, located on the acromion process of each shoulder) were used to calculate an estimated GPS marker position (eGPS) located between the participant's scapulae.

The calculation of estimated GPS marker position (eGPS) was performed as following

$eGPSx = \frac{SH_{Rx}+SH_{Lx}}{2}$ Equation 4

The instantaneous displacement of estimated GPS marker position was calculated in m as following:

$deGPS_{x2} = eGPS_{x2} + |eGPS_{x2} - eGPS_{x1}|$ *Equation 5*

$deGPS_{y2} = eGPS_{y2} + |eGPS_{y2} - eGPS_{y1}|$ *Equation 6*

The displacement (m) of estimated GPS marker (eGPS) from frame to frame was calculated as following:

$deGPS = \sqrt{deGPS_x{}^2 + deGPS_y{}^2}$ *Equation 7*

In cases of incomplete GPS marker data, the sum of GPS and replacement eGPS final frame to frame displacement represents the GPS marker total distance from initial to final position. All values are presented in metres. Trials with both GPS and SH error were omitted from the trial (20%).

*3.3.5 Statistical analysis*

Descriptive statistics are presented as the mean and standard deviation of the distance covered for the three trial protocols (Acceleration, Change of Direction and Zig-Zag) measured concurrently by optoelectronic motion capture system (Qualisys) and three GPS devices (STATSports Viper, Catapult Minimax, GPSports SPI-ProX).

The agreement between the distance measured by the three GPS devices compared with motion capture system was assessed by presenting the bias (raw (m) and percentage values) and standardised by dividing by the criterion standard deviation. Linear regression modelling was used to plot the GPS data against the Qualisys data. R-Squared values indicate a relative measure of fit and the Standard Error of the Estimate (SEE) assessed the absolute measure of fit. Mean standardised bias was used to quantify the magnitude of the difference between the distance measured by Qualisys and that reported by the GPS systems, with bias and SEE qualitative magnitudes classed as <0.2, trivial; 0.2-0.6, small; 0.6-1.2, moderate; 1.2-2.0, large; >2.0 very large (Hopkins, 2000) and used 95% limits of agreement (Bland and Altman, 1986).

### *3.4 Results*

The descriptive data for the three trial protocols and the three GPS devices are shown in Table 3.1. All three GPS devices generally underestimated distance relative to the criterion measure and a small linear relationship is shown across the majority of trial protocols (Figure 3.5, 3.6 and 3.7). The four viper devices overestimated distance for the acceleration protocol (0.51 ± 0.51 m; $R^2$ = 0.12; SEE = 0.32) and multi-direction (ZIG) (1.39 ± 0.38 m; $R^2$ = 0.03; SEE = 0.25) however, there was no reported bias for the shuttle (COD) protocol (0.00 ± 0.76 m; $R^2$ = 0.29; SEE = 0.70). The Minimax device overestimated the ACC (1.79 ± 0.93 m; $R^2$ = 0.02; SEE = 0.36) and ZIG (1.49 ± 1.26 m; $R^2$ = 0.10; SEE = 0.25) protocols and underestimated COD (-0.56 ± 0.70 m; $R^2$ = 0.12; SEE = 0.40). The SPI-ProX device overestimated all three protocols: ACC (0.47 ± 1.12 m; $R^2$ = 0.66; SEE = 0.21), COD (1.14 ± 1.00 m; $R^2$ = 0.06; SEE = 0.41) and ZIG (1.03 ± 0.57 m; $R^2$ = 0.12; SEE = 0.26).

| **Protocol** | **n** | **Qualisys distance (m)** | **Viper distance (m)** |
|---|---|---|---|
| ACC | 31 | 13.2±0.3 | 13.7±0.5 |
| COD | 29 | 39.2±0.8 | 39.2±0.8 |
| ZIG | 36 | 9.2±0.3 | 10.6±0.3 |
| | | | **Minimax distance (m)** |
| ACC | 31 | 13.1±0.3 | 14.9±0.8 |
| COD | 29 | 39.7±0.4 | 39.2±0.7 |
| ZIG | 36 | 9.3±0.3 | 10.8±1.4 |
| | | | **SPI distance (m)** |
| ACC | 31 | 13.1±0.3 | 13.6±0.5 |
| COD | 29 | 39.7±0.4 | 40.9±0.8 |
| ZIG | 36 | 9.3±0.3 | 10.3±0.6 |

*Table 3.1 Descriptive data (mean and standard deviation of the distance covered) for Acceleration (ACC), Change of Direction (COD), and Zig-Zag (ZIG) trial protocols measured concurrently by optoelectronic motion capture system (Qualisys) and three GPS devices (STATSports Viper, Catapult Minimax, GPSports SPI-ProX)*

Validity statistics are shown in Table 3.2. Comparing protocols, data shows a trend of percentage bias being highest in all three devices during the ZIG protocol (11.6 – 16.4%). The only outlier to this from the other trial protocols was found for the Minimax ACC measurement (14.5%). Excluding this, percentage bias was much lower for the COD protocol (1.2 – 2.9%) and ACC protocol (3.3 – 3.5%).

Comparing the three GPS devices, the viper unit performed best during the ACC and COD protocols and the SPI device during the ZIG. The Minimax device generally performed worst across the three protocols. The ACC protocol showed the smallest mean standardised bias (0.56 - 4.29). This is compared with the COD (-1.55 - 4.89) and ZIG protocol (1.32 - 3.67) with majority of data representing a 'very large' difference (>2.0). The best performing protocols showing 'small' (0.2 - 0.6) and 'moderate' (0.6 - 1.2) differences were found using the Viper unit (ACC – 0.97, COD – 0.56).

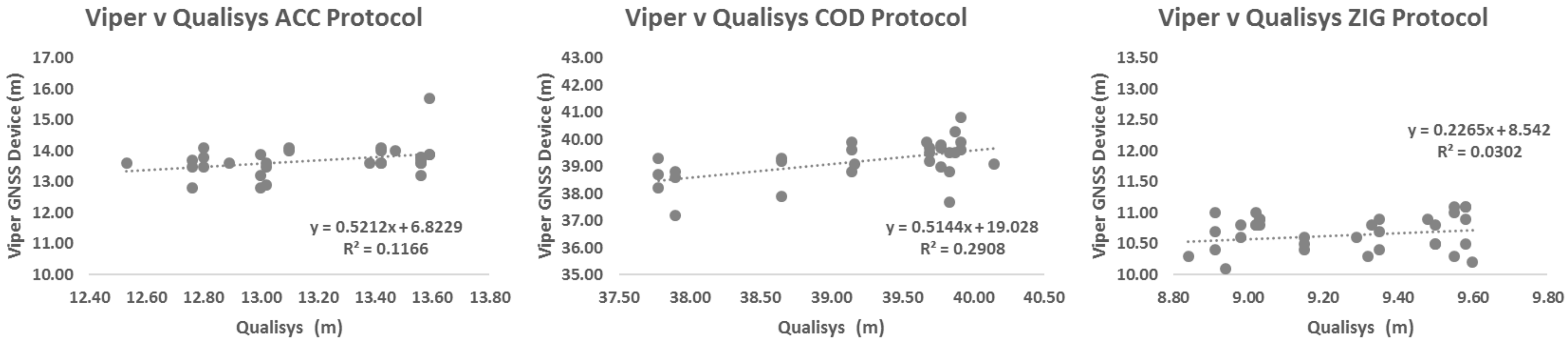



*Figure 3.5 Linear regression plots for Qualisys and Viper GPS device distance measurement of three trial protocols*

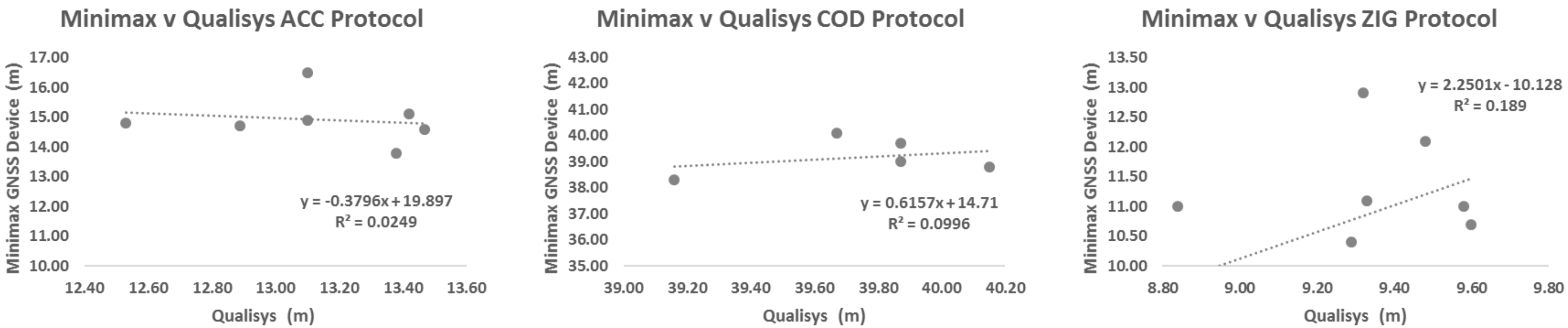



*Figure 3.6 Linear regression plots for Qualisys and Minimax GPS device distance measurement of three trial protocols*

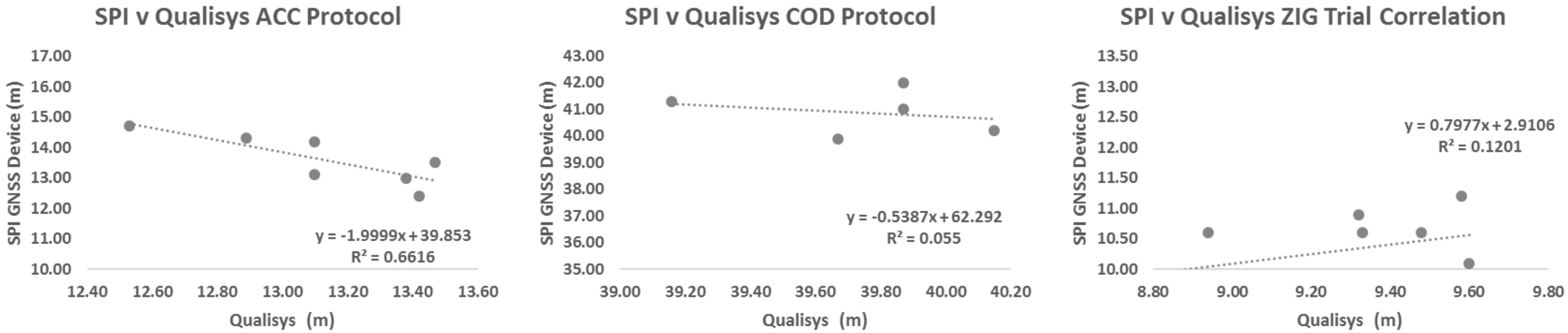



*Figure 3.7 Linear regression plots for Qualisys and SPI-ProX GPS device distance measurement of three trial protocol*

| | Protocol | Bias (m±SD) | % Bias (±SD) | Mean Standardised Bias (±95%CL) | $R^2$ | SEE |
|---|---|---|---|---|---|---|
| **Viper** | | | | | | |
| | ACC | 0.51±0.51 | 3.9±3.8 | 1.46±0.35 | 0.12 | 0.49 |
| | COD | 0.00±0.76 | 0.00±2.0 | 0.00±0.36 | 0.29 | 0.66 |
| | ZIG | 1.39±0.38 | 16.2±4.0 | 5.08±0.47 | 0.03 | 0.33 |
| **Minimax** | | | | | | |
| | ACC | 1.79±0.93 | 14.5±6.7 | 4.89±2.25 | 0.02 | 0.87 |
| | COD | -0.56±0.70 | -1.4±2.5 | -1.55±2.36 | 0.10 | 0.78 |
| | ZIG | 1.49±1.26 | 16.4±13.6 | 4.99±3.26 | 0.12 | 1.30 |
| **SPI** | | | | | | |
| | ACC | 0.47±1.12 | 3.5±9.1 | 1.32±2.98 | 0.66 | 0.52 |
| | COD | 1.14±1.00 | 2.9±2.5 | 3.02±3.29 | 0.06 | 0.95 |
| | ZIG | 1.03±0.57 | 11.6±5.9 | 3.67±1.51 | 0.12 | 0.60 |

*Table 3.2 Criterion validity statistics for Viper, Minimax and SPI GPS devices for each validity trial protocol*

### *3.5 Discussion*

This study analysed the validity of 10- and 15-Hz GPS devices to measure the distance of team-sport specific movements.

The main findings were that all three devices reported moderate to large bias (increased with movement complexity), generally overestimating distance and showed a weak linear relationship relative to a gold-standard measure. Device accuracy was best during unidirectional movement with simple change in direction and decreased with trial complexity (i.e. ZIG). Regarding the comparison across devices, the Minimax 10-Hz device performed weakest across the majority of trials compared with the Viper 10-Hz and SPI-Elite 15-Hz devices. Comparison of data between devices must be approached with caution due to lower number of completed trials for SPI and minimax devices (5 - 9) compared with Viper (31 - 36).

Previous studies have shown that devices, inclusive of those measuring at 1-Hz (MacLeod et al., 2009), accurately quantify distance during team sport simulation and therefore can justifiably be used during team sports matches and training (Scott, Scott and Kelly, 2016). A soccer-specific course was used to assess the accuracy of GPS devices to measure distance, concluding that 1- and 5-Hz devices could be used to quantify distance in soccer and similar field-based team sports (SEE = 2.2 – 4.4) (Scott, Scott and Kelly, 2016). The current study agrees with this research with ACC and COD trials mirroring these levels of error (Table 3.2). Measuring higher speed, acceleration and changes in direction protocols, the GNSS device accuracy decreases along with the validity of its measurement (Grey et al., 2010; Portas et al., 2010; Varley et al., 2011; Akenhead et al., 2013a; Rawstorn, et al., 2014; Duffield et al., 2014). The current study found similar findings, showing poor (>10%) bias with the most complex protocol (ZIG). Caution must be taken when using these devices to measure distance during movements that involve repeated change of direction.

The results of the current study were also in agreement with Rawstorn et al., (2014) that caution is recommended when measuring rapid multidirectional change, shown to be an important part of soccer performance. Video tracking research shows that soccer players sprint (>25.1kph) 51 ± 20 times per match with the average sprint distance of 6.9 ± 1.3 m (Barnes et al., 2014). A player will perform up to 1400 actions during a 90-minute match consisting of short activities changing every 4-6 seconds (Bangsbo, 1994; Stolen et al., 2005). Therefore, practitioners using such metrics in their analysis should be aware of the limitations of technology used to measure these actions shown in this data and previous studies, especially when using slower sample rate devices.

To further develop the findings from those of the previous research, the current study adopted the use of an optoelectronic motion capture system (Qualisys, Gothenburg, Sweden) configured in an outside space (Figure 3.1) to accurately assess criterion validity. Motion capture systems have been shown to measure dynamic movement with error less than 2 mm (Merriaux et al., 2017). Important to this research, the difference between the Qualisys measured distance and the pre-determined measured track for ACC (0.76 ± 0.34 m; 5.9%), COD (2.64 ± 0.81 m; 7.0%) and ZIG (2.75 ± 0.25 m; 34.8%) highlights the extent of protocol deviation from the testing subject (potential human error if criterion measure was not used).

Sample rate has been cited as a key factor in technology development. Early studies used devices sampling at 1-Hz through to current, commercially available devices sampling at 18-Hz (STATSports Apex). The results of previous validity trials have shown higher sampling frequency devices (10- and 15-Hz) to be more accurate and reliable than 1- and 5-Hz units (Scott, Scott and Kelly, 2016). The current study found that the 15-Hz SPI and 10-Hz viper devices performed better than the 10-Hz minimax devices but does not support a higher or lower sampling rate with the number of trials analysed.

The current study was completed with GPS devices that manufacturers have since updated and replaced with newer technology. Several factors including higher sampling rates up to 18-Hz, use of augmentation to boost accuracy, utilisation of accelerometers to enhance movement tracking algorithms and increased satellite availability with the GNSS network, have improved device accuracy (Beato et al., 2018). It is important for research to support technological development, report the accuracy of new devices to give practitioners confidence using GNSS devices to guide the training process and, as outline in this study, employ gold standard methods for this process (Linke et al., 2018). This detailed study focusing on accuracy precision found the average spatial measurement error of a GNSS system was 96 cm (motion capture system used as criterion measure), the RMSE observed (4.9%) when measuring total distance of sports specific movements would correspond to a discrepancy of 560 m across a total match (Linke et al., 2018). The author reported larger errors when measuring high speed performance indicators and recommended research into XY-data, further to metric validity.

The satellite number and HDOP data were not available due to the device version used during testing. Precautions were taken to ensure environment was created for good satellite visibility and signal connection, but no objective evidence can be provided. The optimal conditions were observed for data collection but validity data assumptions cannot be extended to every environmental condition. Additionally, there was limited data collected, especially for Minimax and SPI devices. This was further reduced after Qualisys data processing due to marker drop out, damaged files or missing sections of trial data, which is especially relevant when trying to compare devices. The method used to synchronise the start and end point between Qualisys and the corresponding GPS units, used in a previous study (Duffield et al., 2009) is an additional source of error to be aware of. The extent of the error is proportional to the amount of data collected so the level of error is mitigated firstly by short movement lengths and the mechanisms used to limit the potential for error in data handling highlighted in the methods.

GPS data was obtained from manufacturer software subjected to individual smoothing algorithms. Future study design could overlay raw positional data values from both Qualisys and GNSS devices, potentially using statistical parametric mapping (SPM). SPM was originally developed for the analysis of cerebral blood flow in 3D PET images (Worsley et al., 1992), but has been used more widely in a wide range of biomechanical applications (Pataky, 2010). Another area of future studies could explore the error in relation to other frequently measured metrics collected by GNSS devices to guide training load. Access to manufacturer equations and algorithms would be critical in this process in order to measure raw error rate and translate it to mechanical error. Metabolic metric accuracy would be an interesting area to explore.

### *3.6 Practical applications*

- 10- and 15-Hz devices measured in this study can be used to measure distance covered of soccer specific movements
- Device accuracy decreases when measuring movements that include multiple change of direction

### *3.7 Conclusion*

The main findings of this study were all three GPS devices reported moderate to large bias, generally overestimating distance and showed a weak linear relationship relative to a gold-standard measure. Caution must be observed when using these devices to measure movements that incorporate repeated change of direction but corroborates the findings of previous studies that GPS devices are useful tools to measure team-sport specific movement and can aid practitioners to guide the training process. The use of motion capture as the gold standard criterion measure is key for accurate criterion measure. Future studies should also ensure protocol design matches sport specific profile, maximise trial numbers to ensure robust statistical analysis and look at utilising raw data values. This study provides validity data on units that are still used by sports teams world-wide and provides insight into the methodology of determining device accuracy with a criterion measure.

# CHAPTER 4: THE USE OF DIMENSIONALITY REDUCTION TO DESCRIBE TRAINING LOAD METRICS IN ELITE SOCCER

## *4.1 Chapter summary*

Once established as fit for purpose, GNSS devices can be used to monitor load in soccer and data can provide insight for practitioners in elite clubs to optimise the training process. This chapter will investigate the methods used to present data in a simple format that has context which resonates with key stakeholders. This study contextualises training data using match average data and then streamlines the analysis using dimensionality reduction. Results from match data (elite soccer players from an English Premier League club) were in general agreement with previous match demand research and were applied to training data, offering a method to present data to coaches. Subsequent analysis of contextualised training data used dimensionality reduction to reduce twelve metrics to three new components ('velocity', 'change in velocity' and 'metabolic intensity'). Components were named to represent the metrics associated with each one and together they provide a rounded view of external training load. The three components of training can be applied to future training load data sets by selecting the highest correlation metric or more pertinently to this thesis by applying the component weightings to the data sets to elicit a factor output for each area of training load. This is a methodological focussed chapter to show proof of concept for the use of dimensionality reduction in the subsequent experimental chapters. The methodology demonstrated will be used in Chapter 5 to describe and compare the loading strategies across three seasons of soccer load and analyse the influence of pre-season training load, injury burden and player age on the rate of in-season injury.

### *4.2 Introduction*

Movement analysis has been widely used to examine the activity patterns and physical aspects of soccer in the last twenty years (Reilly and Thomas, 1976; Mohr, Krustrup and Bangsbo 2003; Dogramaci, Watsford and Murphy, 2011). Movement analysis data is commonly used retrospectively by many elite soccer clubs to provide a i) detailed physical breakdown of training or match play, and ii) an objective measure of physical demand placed on a player which can be used for subsequent training load planning.

Training load in team sports can be described as either external or internal (Akubat et al., 2014). Internal load is commonly observed in soccer using the athlete rating of perceived exertion (RPE) and heart rate metrics (Buchheit et al., 2012; Owen et al., 2015). External load metrics, supported by the developments in micro-technologies, are commonly observed through metrics including total distance (m), distance in speed bands (m), number of sprints (count) and acceleration sum (number of actions > threshold) (Clark, 2014). Devices which combine accelerometers and non-differential satellite position receiving chips to produce load metrics are collectively termed integrated technology (Dellaserra, Gao and Ransdell, 2014). The accelerometer provides additional inertial data at up to 100-Hz which can enhance position precision, contributing to manufacturer smoothing algorithms applied during the data processing. The introduction of GNSS analysis in soccer results in more readily available data to coaches, players and support staff to help develop specific training programs and track individual physical progression.

The practical use of data varies widely across different professional soccer clubs. A systematic review of papers (n=43) evaluating the application of position tracking technology showing significant differences in speed zones used highlighted variation in data processing and presentation, often with the analysis of many different metrics (Cummins et al., 2013). The large scope for analysis is intriguing but can become a limitation as multiple, complex data sets can become difficult for practitioners and coaches to digest. Essentially, the overload of potentially unimportant information ultimately limits its usefulness. Presenting absolute training data with no historical reference or context to guide the user can also reduce clarity and effectiveness of data presentation. Researchers aware of these challenges have previously attempted to organise the data analysis process and categorise training load for it to be presented in a simplified format (Owen et al., 2017).

To the authors knowledge there are no studies which have attempted to statistically reduce either the internal or external metrics in soccer. Studies have either selected basic metrics that are shown to be most reliable or use a multi-modal approach to present metrics in two key categories (volume and intensity) based on knowledge of the metrics (Owen et al., 2017). Integrated technology software packages present many different metrics which can be a limitation with data analysis and presentation.

However, to simply select important metrics using opinion could mean that potential correlations between metrics and outcomes are missed.

This study aims to (1) give context to training load data by using individual match thresholds and applying them to training data analysis, and (2) simplify the description of training by identifying pertinent metrics via dimensionality reduction.

## *4.3 Methods*

### *4.3.1 Participants*

Training and match load data were collected from nineteen male elite soccer players (18.8 ± 0.9 years, 74.7 ± 6.3 kg, 179.0 ± 5.0 cm) for one season resulting in 7836 training and match observations. All players were contracted to play professional soccer on a full-time basis at an English Premier League soccer club for the 2013-2014 season. Ethical approval for this research was obtained from the Research Ethics Committee of the University of Bath Research Ethics Approval Committee for Health: REACH reference number: EP 11/12 129. All participants received a clear explanation of the study and signed informed consent forms prior to data collection.

### *4.3.2 Equipment*

All players wore commercially available GPS (10-Hz) and accelerometer (100-Hz) devices (Viper 2, STATSport technologies, Newry, Northern Ireland) for all training sessions and matches. GPS units have been shown to be a valid tool to measure team sport matches and training (Scott, Scott and Kelly, 2016). In line with manufacturer recommendations, devices were worn between the shoulder blades embedded in a custom-made vest. Each player was assigned their own tracking unit for use throughout the study period.

### *4.3.3 Study design*

Load data was collected from each player for every match during the 2013-2014 soccer season. Match data was considered eligible if the player had completed a full 90-minute match on an 11v11 pitch in their normal playing position and the data was absent of positioning error or signal disruption (e.g. signal disruptions in stadia or battery problems with tracking units). Average match data (match threshold) was then established for twelve individual metrics for each player. An average was created based on data from eight matches. Any player with less than eight matches of eligible data (*n* = 3) were excluded at this point. The twelve individual metrics are described in Table 4.1.

| Performance Metric | Measurement Units | Description |
|---|---|---|
| Total Distance | Metres (m) | Simply shows how far a player has moved irrespective of speed or change of direction within a soccer activity. |
| High Speed Running | Metres (m) | The amount of distance covered above 65% of the individual's max speed. Max speed was calculated from a historical search of all speed testing along with training and match GPS data for each individual. |
| High Metabolic Load | Metres (m) | HML is the distance travelled by a player when their Metabolic Power (Energy Consumption per Kilogramme per second) is above the value of 25.5 W/Kg. This value of 25.5 corresponds to when a player is running at a constant speed of 5.5m/s on grass or when they are performing significant acceleration or deceleration activity, for example if they are accelerating from 2 to 4m/s over 1 second. |
| Dynamic Stress Load | Arbitrary Unit | Dynamic Stress Load is the total of the weighted impacts, which is based on accelerometer values of magnitude above 2g. It weights the impacts using a convex-shaped function, an approach similar to that used in the Speed Intensity with the key concept being that an impact of 4g is more than twice as hard on the body as an impact of 2g (Impacts are a mixture of collisions and step impacts while running). It gives a representation of the loading effects on the body and is a potential fatigue marker. Values depend significantly on an individual's running style, therefore comparison between individuals are not always valid. |
| Accelerations/Decelerations | Count of actions above 3 $m/s^2$ | Measured on the basis of the change in GPS speed data and to count as an acceleration/deceleration, the increase in speed must take place for at least half a second with maximum acceleration in the period at least 0.5m/s/s. Viper software settings were set to count actions above 3 $m/s^2$ and omit any accelerations or decelerations below this threshold. |
| Sprints | Count | Number of absolute sprint entries within a soccer activity – classified as above 6.66m/s (in line with threshold ranges set by various studies and used by Prozone for premier league match analysis (Bradley et al., 2009, Harley et al., 2010, Abt & Lovell, 2009) and the sprint has to be maintained for at least 1 second. |
| Average Metabolic Power | W/Kg | Based upon energy expenditure by the players it is the amount expended per second per Kg. The measures combine the energy expenditure associated with constant speed activity as well as acceleration and deceleration activity. It provide better measures for the performance of players who are heavily involved in short sharp running activity, particularly associated with central defenders and midfielders in football. |
| Speed Intensity | Arbitrary Unit | A measure of the total exertion of a player in a session based on the time spent by the player at each of the speed values. Calculation uses a weighting function where speed intensity is the sum of individual zone weighing for that specific time point multiplied by the time interval in seconds between each successive speed point. The higher the speed travelled, the higher speed zone entered, the higher the weighting applied and the bigger the contribution to Speed Intensity. |
| Impacts | Count | The impacts (actions), identified as accelerometer magnitude values above 2g in a 0.1 second period, are totalled to give the number of impacts. |
| Equivalent Metabolic Distance | Metres (m) | Uses the total energy expended and derives from it the distance in metres that an athlete would need to cover at a constant speed to expend the same amount of energy. |
| Energy Expenditure | Kcal | Gives the total energy associated with running only including accelerating and decelerating activity measured in kcal. It is based on the level of activity and scaled by the weight of the player in kilograms. It is important to remember that this is an energy expenditure value based on the speed and acceleration data only and so will be less than the actual energy expenditure value as GPS does not accommodate the metabolic cost of actions such as tackling, heading, kicking, body contact and does not allow for extra energy associated with running sideways or backwards. It also ignores resting metabolic rate and air resistance (both small). It is suggested by STATSports that the figure is approximately 70-80% of the true total energy expended in a soccer activity and this will vary according to session type. |

*Table 4.1 Statsports Viper training load metrics explained – Adopted from STATSports Technologies LTD metrics report, Version 1.2 (2012)*

Training load data was collected for every session for the duration of the 2013-2014 soccer season across the twelve metrics.

To contextualise this data, each of the data points were expressed as a percentage of the match threshold calculated by the following formula:

$$\text{Training Load \%} = \frac{\text{Training Output}}{\text{Match Threshold}} \times 100$$

The training load percentage was then averaged to produce a simple holistic training load value named 'Total Load', also expressed as a percentage.

$$Total\ Load\ \% = \frac{\sum Metric\ Percentages}{12}$$

An example of the visual output is shown below in Figure 4.1:

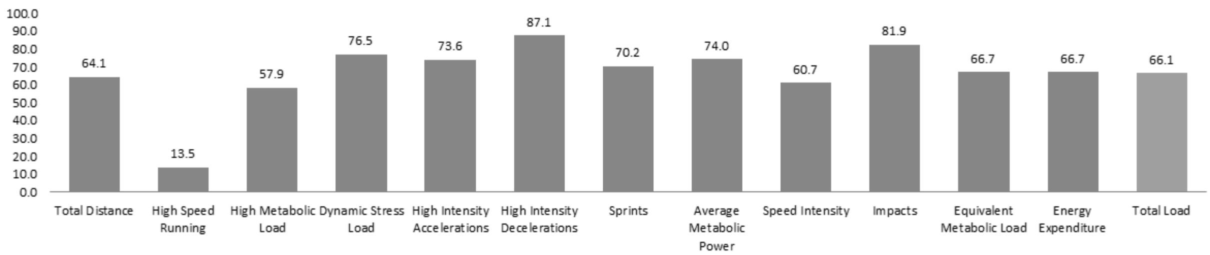



*Figure 4.1 Visual representation of training load metrics for one training session expressed as percentage of match load*

Principal component analysis was then used on contextualised metrics to reduce twelve metrics into new components of load.

*4.3.4 Data analysis*

Software packages used for data processing and analysis were Viper (STATSports technologies, Newry, Northern Ireland), SPSS (IBM SPSS Statistics, Version 19) and Microsoft Excel (2010).

A one-way ANOVA with a Tukey post-hoc test was used to analyse significant differences between playing position for the twelve training load metrics.

The Kaiser-Meyer-Olkin (KMO) measure was used to verify the sampling adequacy for the analysis. It is recommended that an acceptable value is greater than .5 but closer to 1 indicates that the analysis should yield reliable results (Field, 2013). An R-Matrix was used to check for a high correlation between metrics to avoid extreme multicollinearity. The removal process resulted in the removal of three metrics leaving nine metrics to be used for analysis (Field, 2005). The determinant of the R-Matrix was also analysed, and the determinant should be greater than 0.00001, indicating the absence of multicollinearity. Once initial statistical checks were complete, a principal component analysis was conducted (n=1369) and the number of retained components was based on analysis of eigenvalues using Kaiser's criterion of 1 and the subsequent scree plot. The plot is interpreted by accepting the points of inflexion in the line of eigenvalues as justification for retaining that number of components.

### *4.4 Results*

The first aim for this study was to create an individualised match-play average for twelve data metrics to provide context for training data analysis. Table 4.2 shows the mean match play data comparing player positions.

There were statistically significant differences between each positional group for each of the twelve metrics except accelerations ($p=.014$). The Tukey post-hoc test revealed differences between each playing position. Total distance for the centre forward position ($9417 \pm 557$ m) is significantly lower than centre back ($p < 0.001$), centre midfield ($p < 0.001$) and full back positions ($p < 0.001$). There was no significant difference between the wide midfield and centre forward position for total distance ($p = 0.153$). In comparison, the number of sprints for the centre back position ($9.0 \pm 4.5$) were significant lower ($p < 0.001$) than centre forward, wide midfield and full back positions. Figure 4.2 shows a season of contextualised training data for the twelve metrics for one player highlighting the complexity of using twelve data streams.

The second aim of this study was to simplify the description of training by identifying pertinent metrics via dimensionality reduction. The analysis on the contextualised data reduced twelve metrics into group factor components, identifying the most pertinent metrics within those components to explain training load. Initial eigenvalues analysis (Table 4.3) highlighted two components greater than 1.0 meaning the first analysis was conducted with the instruction to produce two component outcomes (68% of variance explained). The subsequent components however were not discounted as the eigenvalue scree-plot analysis (Figure 4.3) indicated the use of three and five component outcomes. It is expected for the components to be somewhat correlated as metric data is from the same session; however, the aim is to reduce the metrics by as much as possible and this is better achieved by discarding the five-component output due to there being a high correlation (.516) between components. Using two components showed an overcrowding of metrics associated with one another which would lead to a lack of session type characterisation. Failing to distinguish between session types could potentially mean overlooking some physical aspects that would be hidden within the data collected. Based on the balance of explanation of total variance, avoiding high correlation between components and ensuring physical demands are represented - twelve data metrics were reduced to three new components. These three simplified components explain 78% of the variance and were independent of each other (.362).

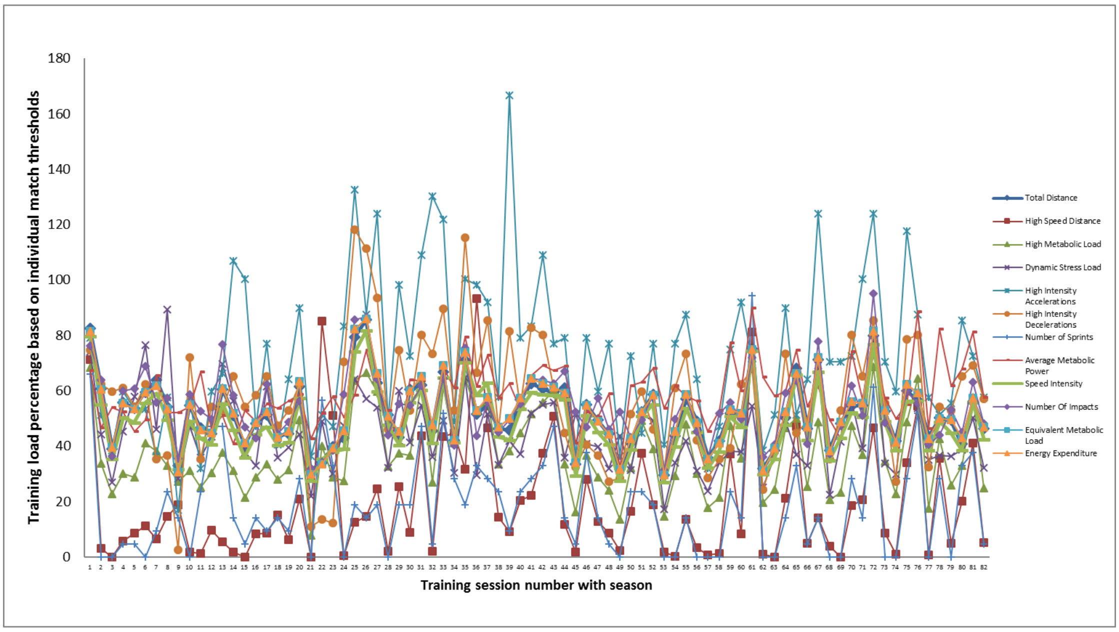



*Figure 4.2 Multiple-metric training data for one soccer player for all completed training sessions during the 2013/14 season*

Table 4.4 highlights how each load metric contributes to the three new components. Due to the association with accelerations (.946) and decelerations (.905), component one is named 'change in velocity'. Component two is strongly associated with number of sprints (.942) and high-speed running (.855) and is subsequently named 'velocity'. Component three was strongly associated with average metabolic power (.868), number of impacts (.571) and speed intensity (.550). This third component of load isolates intensity measures that accumulate across a training session and is therefore named 'metabolic intensity'. These terms were chosen as simple representations of the metrics which contribute to each new component.

| Position | Total Distance | High Speed Running | High Metabolic Load | Dynamic Stress Load | High Intensity Accelerations | High Intensity Decelerations | Number of Sprints | Average Metabolic Power | Speed Intensity | Impacts | Equivalent Metabolic Load | Energy Expenditure |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Centre Back** | 10559±1065 | 465±145 | 1779±350 | 396±206 | 34±9 | 59±12 | 9.2±4.6 | 9.6±0.9 | 521±57 | 7143±2211 | 12536±2211 | 1051±132 |
| **Full Back** | 10473±837 | 509±171 | 1924±247 | 323±54 | 41±10 | 64±16 | 18.9±5.9 | 9.3±0.6 | 522±43 | 5946±972 | 12671±938 | 1086±115 |
| **Centre Midfield** | 10506±626 | 380±139 | 1784±263 | 365±93 | 35±14 | 57±18 | 8.8±4.6 | 9.6±0.7 | 518±34 | 6128±1360 | 12483±776 | 1031±145 |
| **Wide Midfield** | 9934±813 | 568±97 | 1951±204 | 367±71 | 45±15 | 69±16 | 24.2±5.4 | 9.2±0.7 | 495±41 | 5948±953 | 12081±999 | 918±79 |
| **Centre Forward** | 9417±557 | 393±171 | 1716±211 | 466±138 | 37±14 | 59±11 | 16.7±4.9 | 8.6±0.6 | 464±33 | 5651±831 | 11248±752 | 982±61 |
| **Average** | 10197±892 | 460±162 | 1831±251 | 381±128 | 38±13 | 61±15 | 15±7.7 | 9.2±0.8 | 505±47 | 6147±1412 | 12219±1050 | 1016±125 |

*Table 4.2 Descriptive (mean ± standard deviation) data of position specific match output from 16 elite soccer players across one competitive season*

| Component | Eigenvalue | % Variance | Cumulative Variance |
|---|---|---|---|
| 1 | 4.681 | 52.01 | 52.01 |
| 2 | 1.452 | 16.13 | 68.14 |
| 3 | 0.968 | 10.75 | 78.90 |
| 4 | 0.808 | 8.98 | 87.88 |
| 5 | 0.378 | 4.21 | 92.08 |
| 6 | 0.306 | 3.41 | 95.49 |
| 7 | 0.239 | 2.66 | 98.14 |
| 8 | 0.109 | 1.22 | 99.36 |
| 9 | 0.058 | 0.64 | 100.00 |

*Table 4.3 Eigenvalues and percentage of variance explained for each component from principle component analysis*

| | Component | | |
|---|---|---|---|
| | **1** | **2** | **3** |
| **High Speed Distance** | 0.031 | **0.855** | -0.146 |
| **High Metabolic Load** | 0.514 | 0.294 | -0.491 |
| **Dynamic Stress Load** | 0.496 | 0.034 | -0.401 |
| **High Intensity Accelerations** | **0.946** | 0.048 | 0.229 |
| **High Intensity Decelerations** | **0.905** | -0.012 | 0.007 |
| **Number of Sprints** | -0.041 | **0.942** | 0.131 |
| **Average Metabolic Power** | -0.177 | 0.064 | **-0.868** |
| **Speed Intensity** | 0.540 | 0.078 | **-0.550** |
| **Number of Impacts** | 0.531 | -0.086 | **-0.571** |

*Table 4.4 Component correlation matrix from principle component analysis of training data highlighting the strongest associations within each component*

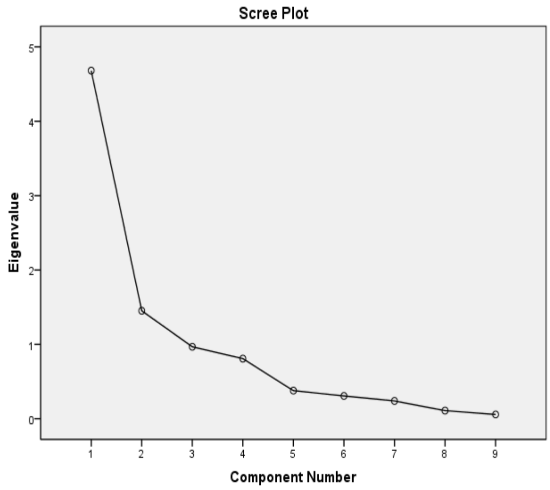



*Figure 4.3 Scree plot of Eigenvalues for each principal component.*

### *4.5 Discussion*

The aims of this study were to compare training load data to individual match thresholds to give context to training data, and to simplify the analysis process by reducing training metrics into load components.

This study is the first to use principal component analysis on elite soccer training data to simplify the data analysis process and identify the most pertinent metrics. Results from the principal component analysis on training data show the twelve metrics reduced to three components named 'change in velocity', 'velocity' and 'metabolic intensity'. Identifying athlete exposure to high velocity work has been linked with both performance (Dunn, 2014) and injury (Askling, Malliaropoulos and Karlsson, 2013). Acceleration is the rate of change in velocity and has been shown to be more demanding on athletes than constant-velocity movement (Osnach et al., 2010). The new component distinguishes acceleration output which can assist practitioners to guide soccer specific programming in order to condition players appropriately for these movement demands. The component names were chosen as simple representations of the metrics which contribute to the three components and collectively the terms symbolise three key areas of training load which put different physical stresses on the player.

Much of the previous research on the physical match demands of soccer use camera based analysis systems (Mohr, Krustrup and Bangsbo, 2003; Di Salvo et al., 2009; Di Salvo et al., 2010) and those that have used position tracking technology have often been carried out on young soccer players who do not play for the same match length (Castagna et al., 2010; Harley et al., 2010). One study which does assess elite adult players using positioning devices reported total distance (10451 ± 760 m) and high-speed running (505 ± 209 m) output (Akenhead et al., 2013b). The present data for total distance (10197 ± 892 m) and high-speed running (460 ± 162 m) is in general agreement with these data. This study also highlighted positional differences in match output similar to previous research (Ekblom, 1986; Bangsbo, 1994; Bloomfield et al., 2007; Di Salvo *et al*., 2007; Bradley et al., 2013). Match data was collected to contextualise each training load observation and obtain a 'total load' observation. This can primarily be used to improve the presentation of data to coaches making the process more effective. It is important that initial education of new data processes takes place. This study uses just one contextual factor (match data) and there are many other factors that could be used to reference external training load (load ratios, session characteristics, player characteristics). An all too common trap is to examine abundant amounts of data in an attempt to find relationships of interest (these may not even exist), without being able to provide the coach or athlete with any meaningful information (Coutts, 2014) This study combats this by offering a methodology to provide a clear, match-specific message. Figure 4.2 shows how complex tracking twelve data streams can be and if presented to a coach, opportunity for a clear message could be lost and potentially any future meaningful information a loss of analysis buy-in. The ability to effectively communicate training load data is paramount – data should be competently analysed and translated into clear, practical messages (Coutts 2014). Implementing three simply named training load components to represent the commonly collected metrics in a simplified format allows practitioners to explore a method to achieve this.

'Velocity' is associated with the amount of work done at high speed which previous research has shown needs to be managed throughout the training week to prevent under or over exposure. With high levels of exposure to high-speed running during a match shown in this study (460 ± 162 m), it is imperative that players are physically prepared for exposure to this stimulus each match-day. High-speed running has been linked with hamstring injury (Askling et al., 2013) and is shown to be the most commonly diagnosed injury in elite soccer (Ekstrand, Hägglund and Waldén, 2011). Risk is elevated when players carry out high volumes of high-speed running during their training micro-cycle however, not performing enough can contribute to the risk being even higher as players will be underprepared for match demands (Dunn, 2014). Additionally, absolute high-speed running actions have increased by ~30% (890 ± 299 vs. 1,151 ± 337 m, $p < 0.001$; ES: 0.82) and sprint actions by ~50% (118 ± 36 vs. 176 ± 46 m, $p < 0.001$; ES: 1.41), in premier league matches (Barnes *et al.*, 2014). Training programmes adapt to the changing demands of match-play to prepare players to perform whilst reducing the risk of injury. 'Velocity', which is strongly correlated with high-speed running and number of sprints, measures player load completed at high speeds and is therefore a useful load component for both injury monitoring and performance.

'Change in velocity' is associated with both accelerations and decelerations which collectively makes up 18% of distance covered (actions >1 m s$^{-2}$) during match-play (Akenhead et al., 2013b). The training and subsequent adaptation of these metrics have been linked with soccer performance (Davis, Brewer and Atkin, 1988; Spinks et al., 2007). Acceleration is defined as the rate of change in velocity (Little and Thomas, 2005) and has been shown to be more demanding on athletes than constant-velocity movement (Osnach et al., 2010). Accelerations have been shown to be fairly homogenous across positions with only wide defenders being the exception who performed the greatest number of maximal accelerations and low velocity accelerations across all playing periods when compared to all other positions ($p < 0.001$) (Varley et al., 2013b). 'Change in velocity' distinguishes acceleration output and could assist practitioners to guide appropriate training for these movement demands.

'Metabolic intensity' is correlated with average metabolic power (.868), number of impacts (.571) and speed intensity (.550). Most strongly associated with average metabolic power, 'metabolic intensity' can isolate an area of player load often underestimated by traditional measurements of running speed particularly evident during small sided games, commonly used in soccer team training (Gaudino et al., 2014). Together all three components provide a rounded view of training load in three clear training components.

There are different approaches to the use of the new components. Firstly, upon analysis of Table 4.4, the metric with the highest correlation in each component could be used to represent that component. Component one would be represented by accelerations (.946), component two by number of sprints (.942) and component three by average metabolic power (.868). This method has used dimensionality reduction to identify these three metrics as the most pertinent out of the original twelve to provide a simplified but directed analysis of training load.

An alternative and more comprehensive application is to apply the components to each data set to create three new physical load representations expressed by component scores. To compute the component score for a given case for a given factor, the standardised score on each metric is multiplied by the corresponding factor loading of the metric for the given factor and then summed together. This will then represent the session weighting for that particular physical load, distinguished by the three new components. Statistics software packages should be utilised to facilitate this process to enable component data to be presented efficiently.

Data analysis in soccer aims to influence training programmes to optimise player performance through reduction of injury incidence or increase in physical capacity. This study has shown techniques to contextualise and simplify the training data analysis process. The use of dimensionality reduction, shown in this study to produce three training load components, could be explored further in future training load research.

Future study would need to assess the validity of the new components across a season long data set. The use of dimensionality reduction could be used to link training load to injury incidence and potentially performance outcomes.

### *4.6 Practical applications*

- Match data can be used to give context to training load data of elite soccer players to simplify the presentation of data communication between the practitioner and the coach
- The methodology used in this study can be applied to other data sets to streamline data analysis

### *4.7 Conclusion*

Dimensionality reduction was used to produce three contextualised training load components that collectively symbolise three key areas of training load, each representing different physical stresses on the player - ‘change in velocity’, ‘velocity’ and ‘metabolic intensity’. The study used match average data to add context to training load communication and dimensionality reduction to simplify the metrics available to practitioners which can be subsequently utilised to improve the decision-making process and affect the training process. Pertinent to this thesis, this was a methodological focussed chapter to show proof of concept for the use of dimensionality reduction for use in the subsequent experimental chapters.

# CHAPTER 5: SEASON-TO-SEASON TRAINING LOAD CHANGE IN ELITE SOCCER

### *5.1 Chapter summary*

Dimensionality reduction provides a simplified method to enhance the practitioner-coach data feedback process and these methods were explored in Chapter 4. In this study, the principles used were applied to training data from an elite Australian soccer club across three seasons. This chapter provides insight to how the proposed methods explored in the previous chapter can be utilised with longitudinal data from elite soccer.

Training load metrics (using a similar method shown in Chapter 4) were reduced to formulate three new components named volume load, speed load and density load. The three new components were used to analyse the distribution of cumulative load over three seasons and also within micro-cycles, analysing specific strategies to manipulate load. Additionally, the three components, age and injury burden were analysed using survival analysis to investigate the effects of pre-season training on in-season injury rate. Results were in agreement with previous research that higher accumulated training load during pre-season resulted in a longer estimated period before in-season injury incidence. The study goes on to highlight a number of strategies used within elite soccer clubs which lead to the changes in training load shown in the data across the three seasons. Conscious manipulation of training loads over an extended multi-season period may influence team injury rates in elite soccer. This study benefitted from the piloting of methodological process (Chapter 4) and focussed on linking analysis of data to applied concepts within an elite soccer club's data set.

### *5.2 Introduction*

Periodisation in soccer encompasses the strategic manipulation of training stress to produce a desired outcome. For elite soccer teams this is to maximise squad availability while optimising player readiness for matches, ensuring that each player has the physical capability to implement the required tactics successfully (Walker and Hawkins, 2017). A well-planned progressive training programme with variation in frequency, duration, intensity and type of activities should be implemented to aid these goals (Jaspers et al., 2017). Programming load creates unique challenges for coaches to balance the requirements of recovery, developing and maintaining physical fitness and skill, and adjusting the training load for freshness before each match (Gastin et al., 2013). It is normal for elite soccer clubs to programme training load using a structured micro-cycle to prepare physically and tactically for match-day (Malone et al., 2015; Thorpe et al., 2016; Los Arcos et al., 2017). A micro-cycle period is often between three and fourteen days, with natural variation dependant on match turn around (Anderson et al., 2015; Malone et al., 2015). Training load therefore, is monitored with the aim of making evidence-based decisions on appropriate loading schemes to enhance desired successful outcomes (Akenhead and Nassis, 2016).

Training load in team sports can be described as either external or internal (Akubat et al., 2014) and the relationship between both has received increasing attention in the literature (Gaudino et al., 2015; Terreño et al., 2016; Jaspers et al., 2017; Akubat et al., 2018). Internal load is commonly recorded in soccer using the athlete rating of perceived exertion (RPE) and heart rate metrics (Buchheit et al., 2012; Owen et al., 2015; Clemente et al., 2017; Djaoui et al., 2017). As described in Chapter 4, external load metrics, measured by technology platforms like GNSS, are objective measures of the work performed by the athlete during training or competition and are assessed independently of internal workloads (Bourdon et al., 2017). Pertinent to this study, metrics informing practitioners of load output include total distance, distance in speed bands, number of sprints and acceleration permutations (Clark, 2014; Clemente et al., 2018).

Despite the increase in training load research especially related to soccer, little detail is known about how the metrics of load and methods of analysis are actually used at elite clubs (Weston, 2018). In elite soccer clubs, decision-making metrics which influence training load include match minutes and the upcoming fixture schedule, with accumulated total load and player subjective feedback ranking below these for popularity amongst practitioners (Akenhead and Nassis, 2016). For any physical load data there is a wide range of possibilities for analysis, however practically this can become a limitation mainly due to its complexity and multiple interpretations. Simplifying and streamlining existing monitoring processes could alleviate some of the limitations in load monitoring (Chapter 4).

Where multiple, complex data analyses are used, it can become difficult for practitioners and coaches to assimilate. The overload of potentially unimportant information ultimately limits its usefulness especially when many of the training load metrics collected have been shown to likely be correlated (Weaving et al., 2018). Principal component analysis (PCA) is a dimensionality reduction process that reduces a set of possible correlated predictor metrics to a smaller number of uncorrelated metrics. This transformation can combat some of the problems associated with multi-collinearity (Kuhn and Johnson, 2013) and has been used in previous studies of training load monitoring (Chapter 4; Weaving, et al., 2014; Carey et al., 2018).

Training load has been linked with performance changes (Mujika et al., 1996; Gastin et al., 2010; Gastin et al., 2013; Lazarus et al., 2017; McCaskie et al., 2018; Graham et al., 2018) and injury risk in team sports (Gabbett, 2010; Gabbett and Jenkins, 2011; Rogalski et al., 2013; Colby et al., 2014; Cross et al., 2016; Carey et al., 2017). Consequently, in today's elite team sports, performance staff reflect on the association between various load metrics and player's capacities to resist decline in performance or an increase in injury incidence (Meyer and Impellizzeri, 2015).

In elite sport, player availability is important and has been shown to impact overall team success (Eirale et al., 2012; Hagglund et al., 2013b; Bengtsson et al., 2013; Podlog et al., 2015; Raysmith and Drew, 2016). Player availability has substantial financial implications; the total wage bill for injured players in the English Premier League for the 2018/19 season reached £166 million (Forbes, 2019). Due to the financial and performance pressure of player availability there is potential danger to under-train (low chronic load) and therefore under-prepare players for match play, which has been shown to increase injury risk (Hulin et al., 2016; Murray et al., 2017b; Windt et al., 2017; Bowen et al., 2017; Gabbett, 2018). In addition, current trends show high training loads, reduced training load fluctuations and attention to how athletes progress to high load may be protective of injury (Hulin et al., 2013; Hulin et al., 2015; Veugelers et al., 2015; Gabbett et al., 2016a; Gabbett et al., 2016b; Stares et al., 2018).

Training load fluctuation can be the result of multiple factors. For example, fluctuation can be due to micro-cycle scheduling between match day turnaround (Los Arcos et al., 2017) or when players join up with their international teams. Training load can also fluctuate with a change in coach, which has shown to result in increased skeletal muscle injury incidence (Donmez et al., 2018). A common training load fluctuation occurs when players suffer from injury and go through a re-conditioning process. After training load fluctuation, it is advised that players are managed conservatively to gradually increase load back to high levels (Stares et al., 2018).

Pre-season is a phase of the elite sport calendar that exposes players to load fluctuation and progression from the off-season phase. The period is often highlighted as an important phase with the main goal to prepare teams for the impending competition phase (Jeong et al., 2011). It is a phase where fitness can be improved without the need to allow for recovery from competitive matches (Gamble, 2006) however, programming training can be challenging to prescribe load that both maximise positive physiological adaptations, while avoiding overtraining and injury (Buchheit et al., 2013).

Players completing a higher proportion of pre-season training are shown to achieve higher in-season training load and greater training and match participation (Murray et al., 2017b). In addition, late pre-season training is associated with the early in-season period performance measured as the first four matches (McCaskie et al., 2018).

Survival analysis is a method used to examine the link between pre-season training load and in-season injury, where the outcome metric is time until an injury occurrence. It has previously been used to analyse the time to first injury across elite Australian football match play and training (Fortington et al., 2017) and to assess the effectiveness of return-to-play programming with time to subsequent injury analysis (Stares et al., 2018). It is well documented that two of the highest risk factors for injury are previous injury (Arnason et al., 2004; Hagglund et al., 2006; Engebretsen et al., 2010a; Engebretsen et al., 2010b; Hagglund et al., 2013) and older age (Arnason et al., 2004; Hagglund et al., 2006; Hagglund et al., 2013a), and is important to consider them when analysing associations between training load and injury.

The aims of this study are to: (1) use dimensionality reduction to simplify the description of training, (2) describe and compare the loading strategies across three seasons of training and match load from an elite soccer team, and (3) analyse the influence of pre-season training load on the rate of in-season injury in elite soccer players.

## *5.3 Methods*

### *5.3.1 Data collection*

Training load data were collected from 56 male elite soccer players competing in the highest level of competition in Australia (mean ± SD age at first record - 22.6 ± 5.4 years). Players were monitored for three seasons, resulting in 86 player seasons of data collected and 11,141 total training and match observations. Ethical approval for this research was obtained from the University of Bath 'Research Ethics Approval Committee for Health' (REACH - reference number: EP 11/12 129). Signed subject consent was obtained from each player for analysis and publication of de-identified data.

All players wore commercially available devices during all field-based training sessions and matches. Devices available for use during season one were GPS-enabled (10-Hz) and accelerometer (100-Hz) devices (Viper 2, STATSport technologies, Newry, Northern Ireland). Devices worn during season two and three were GNSS-enabled (10-Hz) and accelerometer (600-Hz) devices (Apex, STATSport technologies, Newry, Northern Ireland). Research has highlighted the limitation of the devices used in season one but has justified it's use to measure team sport-specific movement (Chapter 3; Coutts and Duffield, 2010; Beato et al., 2016; Scott et al., 2016). Apex devices have shown good levels of accuracy (bias < 5%) in sport specific metrics and can therefore be used to quantify players' workload during training sessions and to optimise the overall training periodisation (Beato et al., 2018). Data lost due to unit or user error (172 observations – 1.54%) were estimated by using an individual average for that subject referenced to the session type (highlighted in Figure 5.4). The pre-season training period was defined as all sessions before the first Football Federation Australia Cup match each season.

### *5.3.2 Injury definition*

Injuries were recorded and classified by club medical staff using the Orchard Sports Injury Classification System (OSICS). Injuries sustained were classified according to the mechanism (contact or non-contact), body part and severity (days missed from activity). This study used the 'time loss' definition; 'an injury that results in a player being unable to take a full part in future football training or match play' (Fuller et al., 2006). Therefore, injuries pertinent to this study were time-loss and non-contact. All other injuries including all traumatic, contact events were excluded from analysis.

### *5.3.3 Principal component analysis*

Principal component analysis was applied to the training load metrics: duration (min), distance (m), high speed (>19.8 km/h) running distance (m), sprint (>25.2 km/h) distance (m), high metabolic load (>25.5 W/kg) distance (m) (HMLD), number of accelerations and decelerations above 3 m/s$^2$, and relative distance (m/min). A broad range of training load metrics was included in the principal component analysis to capture as much information about the physical demands of the session as possible. Although there is no universally adopted approach for training load assessment in high-level football the top-five-ranking metrics used included accelerations (various thresholds and both positive and negative), total distance (m), distance covered above 5.5 m/s (>19.8 km/h) and estimated metabolic power (Akenhead and Nassis, 2016). The choice of load metrics was also informed by previous studies reporting associations between high-speed running distance and acceleration with injury risk (Gabbett, 2010; Gabbett and Jenkins, 2011; Rogalski et al., 2013; Colby et al., 2014; Cross et al., 2016; Carey et al., 2017). An 80% threshold of the cumulative variance explained was used to determine the number of principal components to retain for the survival analysis (Jolliffe, 1986).

The three new components were used to analyse the distribution of cumulative load over each of the three seasons using both a four- and twenty-one-day rolling average. The distribution of load between the load micro-cycles from match-day working back through to five days prior to the match (M-1 to M-5). This study evaluated the increase and variation in loads that were a result of programming interventions and external effects including an internally named strategy to increase chronic training load (seasonal creep), the manipulation of the weekly training load schedule and loading pattern to prepare for matches (micro-cycle manipulation) and also the effect of changing coaching staff on the change in training load.

### *5.3.3 Survival analysis*

The Cox proportional hazards regression model was used to estimate the effects of cumulative pre-season training load, pre-season injury burden, and player age on time to first injury during the in-season period. Cumulative training load was represented by summing each of the retained principal components over each pre-season session for each player. Injury burden was represented by the number of pre-season training sessions missed due to injury. This number did not include sessions missed for non-injury reasons such as international team duties. Age was computed at the end of each pre-season period. In-season exposure time (in hours) was accumulated after each training session or match until either a player sustained an injury, or the end of the season was reached (censored observation). Robust sandwich estimators were used to calculate standard errors due to repeated observations of players across multiple seasons (Therneau and Grambsch, 2000). Players were excluded from the survival analysis if they were signed during the competition cycle (i.e. their pre-season load was conducted away from the club and could not be monitored). All analyses were performed using the R statistical programming language (version 3.5.1) (R Core Team, 2018) utilising factoextra, FactoMineR, ggplot2 and survival as the principle packages.

## ***5.4 Results***

*5.4.1 Principal component analysis*

The variance explained by each principal component is shown in Figure 5.1. The scree plot (Figure 5.1) indicates that much of the variance in the training load data (11,141 observations of 8 metrics) could be explained in one dimension (67.6%). Combined, the first three dimensions explained 88.2% of the total variance.

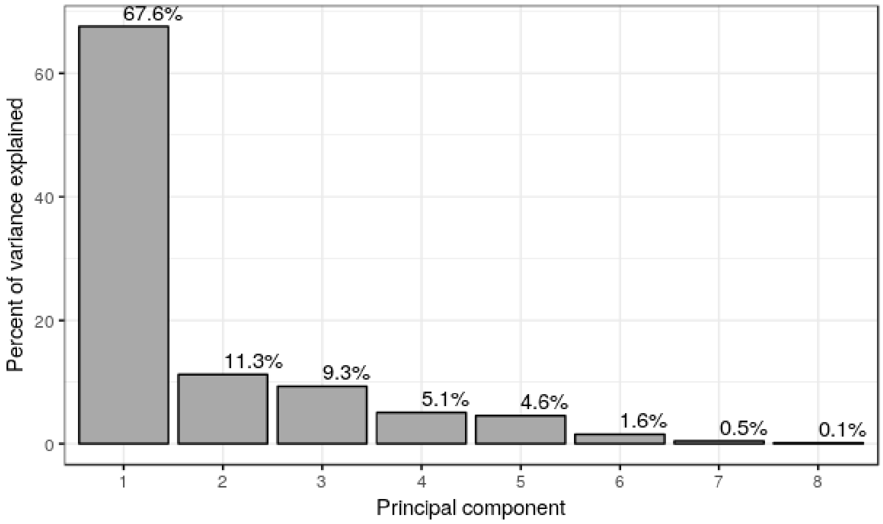



*Figure 5.1. PCA Scree plot showing percentage of variance explained by each principal component*

Variable factor maps (Figure 5.2) show how each training load metric was related to the first three principal components.

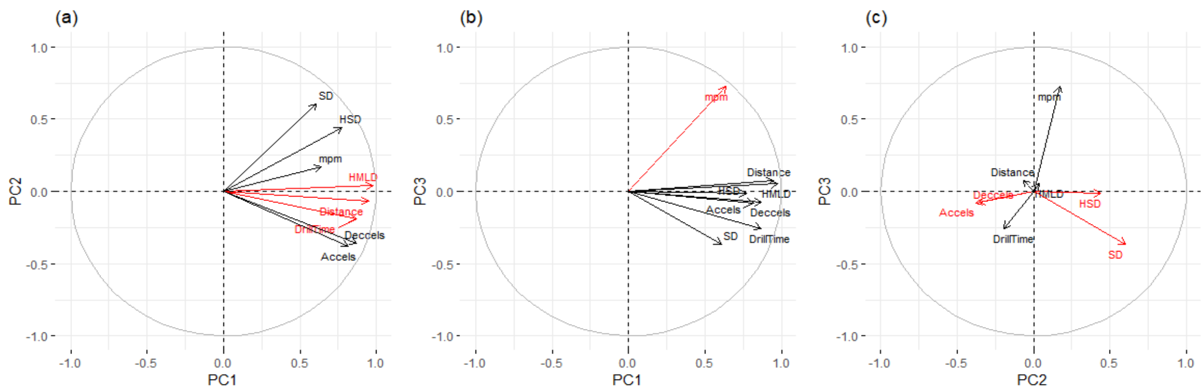



*Figure 5.2 Variable factor maps showing how each training load metric is related to principal components (a) PC1 and PC2, (b) PC1 and PC3, (c) PC2 and PC3. The highest correlated metrics against the three principal components are highlighted in red*

| Metrics | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 |
|---|---|---|---|---|---|---|---|---|
| **Drill Time** | 0.868 | 0.193 | -0.256 | -0.322 | 0.140 | 0.077 | 0.079 | 0.049 |
| **Distance** | 0.948 | -0.069 | 0.075 | -0.242 | 0.155 | 0.018 | -0.035 | -0.083 |
| **High Speed Distance** | 0.771 | 0.441 | -0.014 | -0.091 | -0.446 | -0.009 | 0.061 | -0.013 |
| **Sprint Distance** | 0.608 | 0.603 | -0.365 | 0.242 | 0.273 | 0.002 | 0.000 | 0.000 |
| **High Metabolic Load Distance** | 0.978 | 0.040 | 0.051 | -0.066 | -0.092 | -0.033 | -0.156 | 0.044 |
| **Accelerations** | 0.818 | -0.378 | -0.078 | 0.350 | -0.120 | 0.211 | 0.002 | -0.010 |
| **Decelerations** | 0.871 | -0.358 | -0.077 | 0.185 | -0.003 | -0.268 | 0.043 | -0.002 |
| **Metres Per Minute** | 0.639 | 0.169 | 0.726 | 0.090 | 0.155 | 0.023 | 0.048 | 0.021 |

*Table 5.1 Raw correlation values for each metric across each principal component. PC1 – PC3 were selected as new components*

PC1 appears to represent total session training volume, as it is positively correlated with all load metrics. Raw correlation values (Table 5.1) show distance (.948), drill time (.876), and HMLD (.977) were most strongly correlated with PC1 suggesting it is representing volume more than intensity of training.

PC2 discriminates between sessions that had inflated high-speed output highlighted by sprint distance (.603) and high-speed distance (.440) versus those that had high amount of accelerations (-0.378) and decelerations (-0.358). This suggests PC2 might be capturing the difference between training sessions or drills with more open space that allowed players to accumulate high speed running load and those that were more confined and produced high acceleration and change of direction counts.

PC3 is strongly correlated with relative distance (m/min) (.726) capturing intensity and could be used as a representation of the ‘density’ of the measured load.

PC1, strongly correlated with distance, session duration, and HMLD explained 67.6% of the variance and due to the associated metrics is named ‘volume load’. PC2, correlated with sprint distance (m > 25.2 km/h) and high-speed distance (m > 19.8 km/h), is named ‘speed load’. PC3, distinguished by relative distance (m/min) which highlights the ‘density’ of distance covered within a session and is therefore named ‘density load’.

### *5.4.2 Distribution of cumulative loads over a season*

Cumulative volume load, speed load and density load for 4 and 21 days longitudinally over the three seasons are shown in Figure 5.3. Volume load 4- and 21-day cumulative load analysis shows a season on season increase in load especially during the pre-season (shown by orange data points) in season three (S3). Cumulative speed load was lower in S3 pre-season compared to in-season period. Cumulative density load shows a downward trend through all three season macrocycles especially evident in S3. To reference the change in load over the study period the mean values from all training and matches for the respective components for all players are 0.010 (volume load), 0.051 (speed load) and -0.0103 (density load).

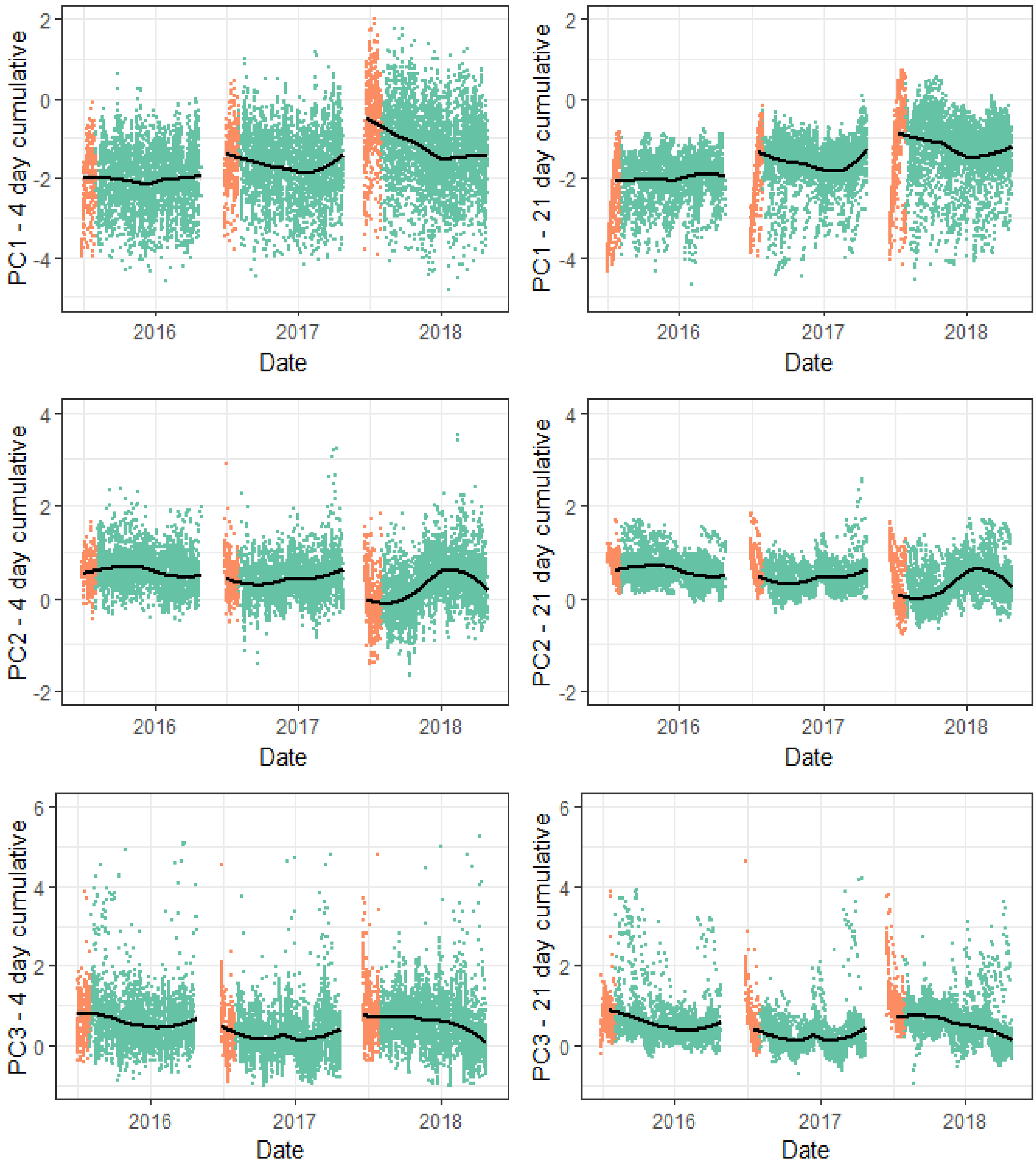



*Figure 5.3 Cumulative training load plots across three seasons. PC1 (volume load), PC2 (speed load) and PC3 (density load) rolling average over 4 days and 21 days.*

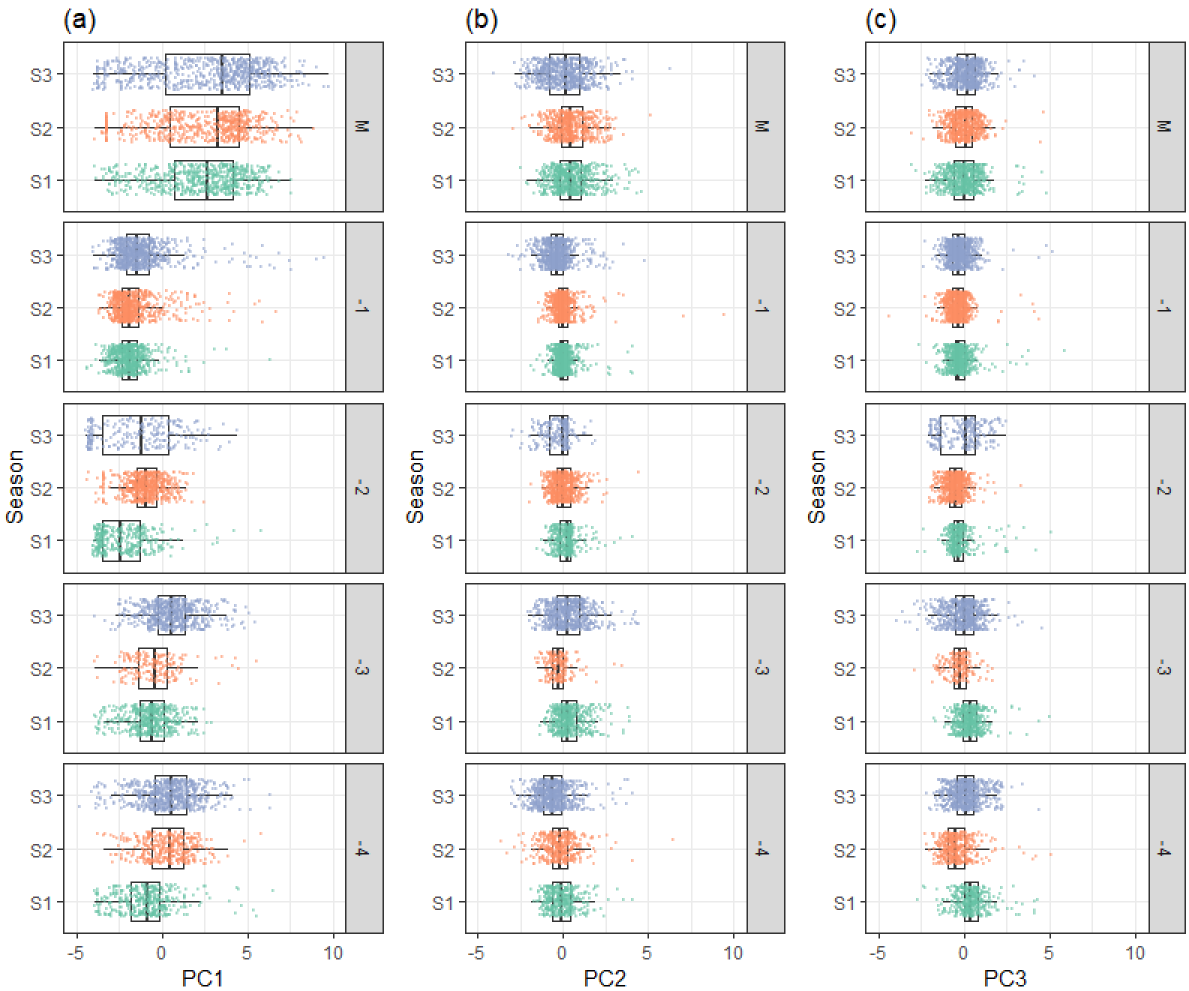
*5.4.3 Distribution of load within micro-cycles*

The distribution of volume load, speed load and density load within matches (M) appears similar across all three seasons (Figure 5.4 - top panel). The values and subsequent percentage changes are shown below in Table 5.2:

| Component | Season 1 Mean PC Score ± SD | S1-S2 Change (Cohens D) | Season 2 Mean PC Score ± SD | S2-S3 Change (Cohens D) | Season 3 Mean PC Score ± SD | S1-S3 Change (Cohens D) |
|---|---|---|---|---|---|---|
| **Volume Load** | 1.375 ± 1.85 | 0.41 | 2.19 ± 2.13 | 0.45 | 3.18 ± 2.21 | 0.88 |
| **Speed Load** | 0.41 ± 0.55 | -0.08 | 0.35 ± 0.87 | -1.80 | -0.91 ± 0.51 | -2.46 |
| **Density Load** | 0.49 ± 0.62 | -0.05 | 0.39 ± 0.58 | 0.64 | 0.70 ± 0.38 | 0.55 |

*Table 5.2 Mean component values comparing match load (full-matches played) between three seasons for PC1 (volume load), PC2 (speed load) and PC3 (density load)*

Plots in Figure 5.4 provide more details on the load trends shown in Figure 5.3; for example, a trend to the right for the main conditioning days (volume load) within a soccer micro-cycle (M-3/M-4), indicates an increase in training volume from S1, S2, or S3. Consistency in load through the 'taper period' of micro-cycle (M-2/M-1) is also highlighted with little variation shown between (speed load and density load).



| |
|---|
| M Denotes when a player competes in a soccer match |
| −1 Training sessions completed 1-day prior to matchday. Often short in nature to minimise fatigue |
| −2 Training sessions completed 2-days prior to matchday. Often tactical in nature but varies with coach philosophy |
| −3 Training sessions completed 3-days prior to matchday with opportunity for conditioning |
| −4 Training sessions completed 4-days prior to matchday with opportunity for conditioning |
| *All sessions are not impacted by previous matches in microcycle so conditioning sessions would not be affected by recovery phase (usually 2-days) |

*Figure 5.4 Box Whisker plot showing distribution of training load (represented by (a) PC1 (volume load, (b) PC2 (speed load) and (c) PC3(density load) within micro-cycles across each season. Comparisons are represented by number of days to matchday (Indicated by key) and across S1, S2 and S3.*

*5.4.4 Relationship between pre-season load and injury rate*

A total of 56 complete player-seasons (pre-season load and in-season time to first injury) from 39 unique players were included in the survival analysis. A breakdown of basic injury results is shown in Table 5.3. Figure 5.5 shows the estimated hazard ratios from the Cox proportional hazard regression model for volume load, speed load, density load, pre-season injury (sessions missed) and age (computed at the end of each pre-season period). Larger cumulative pre-season training volumes were associated with a small reduction in in-season injury hazard rate with all three upper confidence intervals below 1.0. Older players typically had slightly higher injury rates, and changes in pre-season session availability or age did not show a clear relationship with in-season injury hazard.

| | **Season 1** | **Season 2** | **Season 3** | **Season 1** | **Season 2** | **Season 3** |
|---|---|---|---|---|---|---|
| | **All injuries** | | | **Injuries meeting definition** | | |
| **Exposure (Hours)** | 4139 | 4468 | 5127 | 4139 | 4468 | 5127 |
| **Injury Occurrences** | 44 | 24 | 35 | 31 | 16 | 18 |
| **Match injuries** | 24 | 10 | 20 | | | |
| **Injury incidence (/1000 hours)** | 10.6 | 10.4 | 17.9 | 7.5 | 3.6 | 3.5 |

*Table 5.3 Descriptive injury data for all and definition specific injuries highlighting total incidence, relationship to exposure incidence for match play*

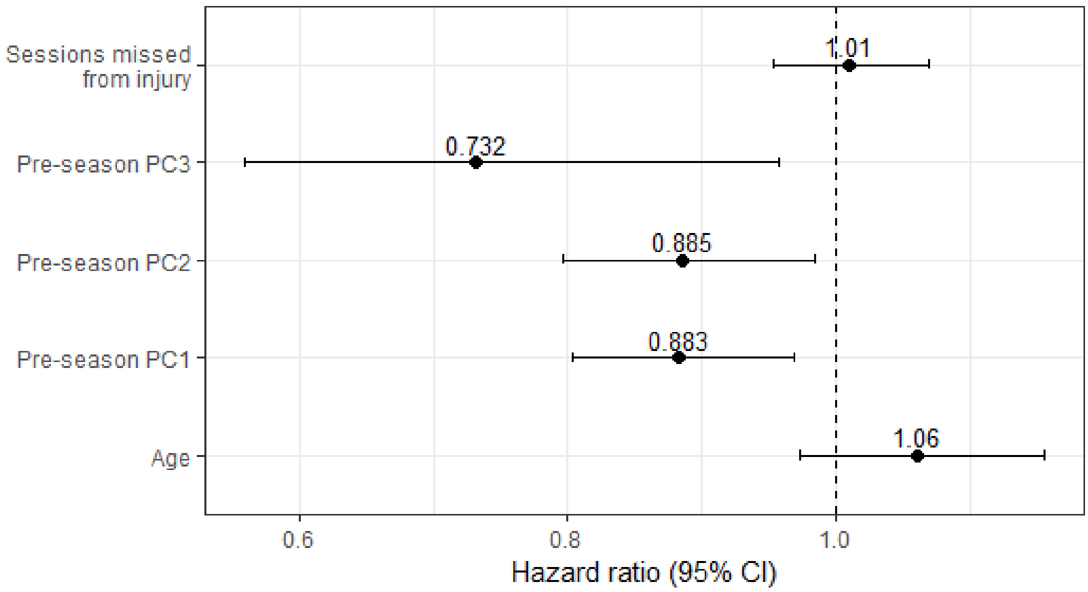



*Figure 5.5 Hazard ratios and 95% confidence intervals for the effects of pre-season training (quantified using principal component scores) on in-season injury rate.*

### *5.5 Discussion*

Dimensionality reduction was used to describe variability among observed, correlated metrics and therefore simplify the description of training for an elite soccer team. New dimensions were used to describe and compare the loading strategies across three seasons of training and match load. Finally, this study analysed the influence of pre-season training load, injury burden and player age on the rate of in-season injury finding that higher accumulated training load (measured by new components) during pre-season resulted in a longer estimated period before in-season injury incidence.

*5.5.1 Dimensionality reduction of training load data*

The ability to effectively communicate training load data is paramount – data should be competently analysed and translated into clear, practical messages (Coutts 2014; Weston, 2018). The communication process can be more effective by reducing the number of reported metrics therefore negating the risk of ‘data overload’ (Coutts, 2014; Weaving et al., 2014; Robertson et al., 2017; Weaving et al., 2018). This study used a principal component analysis (PCA) and was able to explain a large fraction (88.2%) of the variance from eight training load metrics using a reduced set of only three new derived components. This was similar to previous studies implementing PCA, where the first two components account for 76.66% of the variance (Weaving et al., 2018) and following the same methodological principles as those highlighted in Chapter 4. The identification of three simply named training load components to represent commonly collected metrics therefore proposes a method of training load data analysis and communication aiming to maximise evidence-based decisions on appropriate loading schemes to enhance the desired successful outcomes (Akenhead and Nassis, 2016). The terms volume load, speed load and density load were chosen as simple representations of the metrics which contribute to each new component.

### *5.5.2 Pre-season load and injury rate*

This study used three new monitoring components; volume load, speed load and density load to analyse whether pre-season training load influences rate of in-season injury in elite soccer players.

Results indicate that higher accumulated training load during pre-season resulted in a longer estimated period before in-season injury incidence (Figure 5.5). This is similar to previous studies in Rugby League showing players completing more pre-season sessions decreased injury risk by up to 17% (Windt et al., 2017). A study analysing the relationship between pre-season training load and in-season availability in Australian football found completing a greater proportion of pre-season sessions resulted in a greater pre-season training load. The subsequent result of this was the ability to perform higher in-season training load which is positively associated with greater match availability (Murray et al., 2017b).

The effect of pre-season injury burden on in-season injury rate was analysed to isolate this factor from the effect of training load effect. The protective effect of increased pre-season training load (Figure 5.5) is not mirrored by the effects of injury burden during the pre-season period meaning there was no association between pre-season injury and in-season injury risk. Future research with a higher number of pre-season injuries could elucidate these trends further. The effect of player age on time to first injury was also analysed as part of the survival with results showing no significant effect on injury rate.

It is important to consider that training load is only one factor that contributes to why a soccer player suffers an injury or not on any specific training or match-day. Injury aetiology models highlighted in Chapter 2 show that there are many other modifiable and non-modifiable factors that need to be deliberated. These include physical capacities (strength, aerobic fitness, tissue resilience), anatomy, gender and psycho-social issues – all of which could separately or collectively influence the training load effect or risk on any given day (Windt and Gabbett, 2017).

### *5.5.3 Strategies for increasing training load*

Match demands did not vary significantly over the three seasons examined in this study highlighted by minimal change in volume load. Table 5.2 does show a large decrease (interpreted by Cohen’s d effect size) in speed load between season two-three (-1.8) and one-three (-2.46) which could be due to the playing style of the team or changes to personal in certain positions.

‘Seasonal creep’ is an internally termed intervention to raise chronic training load which is visually highlighted by the 4- and 21-day cumulative load graph for volume load (Figure 5.3), especially during the pre-season macro-cycle. Volume load for conditioning training sessions (M-3 and M-4) from season one to season two increased by 3.07% (1.388 – 1.432) and from season two to season three by 3.24% (1.432 – 1.480). Conscious decisions were made to progressively increase the on-field load each season starting from the pre-season base load, in order to aid technical, tactical and physical performance improvement with the added intention of improving player robustness (decreasing injury incidence). Previous research has shown high chronic load is protective against injury (Hulin et al., 2016; Murray et al., 2017b; Windt et al., 2017; Bowen et al., 2017; Gabbett, 2018) and is associated with better performance (Gabbett, 2018). During the period of data analysis this was driven by consistent staffing within the sports science and performance department to build on previous season programming.

Cumulative speed load was lower in the pre-season of season three compared to the in-season period. This is an example of how the new components can distinguish between different training stresses. The physical goal of pre-season three to increase volume of distance covered (m) and short intensive actions measured by acceleration and deceleration count (> 3 m/s2). This is shown by an increase in volume load and a concurrent decrease in speed load, as high-speed output (m > 19.8 km/h) could not match the increase of the other physical metric outputs (Figure 5.3). Interestingly, this balanced out during the competition phase macro-cycle, which questions the effect of varying pre-season training modalities on in-season high speed running capacity.

Season three load highlights a downward trend measured by ‘density load’. Practitioners continually strive to find the balance between match-play freshness, seasonal fitness maintenance with micro-cycle optimisation and combating cumulative fatigue across seasonal competition (Walker and Hawkins, 2017). Potential further research could investigate the balance of in-season training load to maintain high levels of fitness throughout the whole season.

This study highlights season-season load change distributed across micro-cycle training days in an elite soccer team (Figure 5.4). This data highlights continuity in match load but an increase in volume load for the main conditioning days within the soccer micro-cycle and therefore in the training output from S1 to S3. In addition to the increase in load through ‘seasonal creep’, seasonal variation in load between training days can be explained by the second load planning approach, internally termed ‘micro-cycle manipulation’. Common micro-cycle periods for Australian elite clubs run for six, seven or eight days due to one-match per week scheduling for the majority of the season with matches programmed on a Friday, Saturday or Sunday (Hyundai A-League Fixtures, 2018). The practice of micro-cycle manipulation was the changing of the natural training micro-cycle to match needs and characteristics of the current squad (age, fitness level, match minutes played, injury history, and tactical needs). This process occurred multiple times throughout the monitoring period. For example, in season one, due to a high injury carry over from the previous season, training load was maximised by the inclusion of two conditioning training days on M-4 (match-day minus four days) and M-3 with a day off-pitch programmed M-2. After higher availability and higher training load in pre-season two, an off-pitch day was programmed M-3 to maximise the tactical lead in to match-day. These manipulations could be the reason for the variations in load between seasons shown across micro-cycle days for speed load and density load. It would be of interest to apply this analysis method to data sets from other leagues in different countries where the micro-cycle may differ with an increased density of matches within the schedule.

The third factor observed was the effect of changes in coaching staff. Between season one and season two, there were changes to the assistant coaches and between season two and three, the head coach. These changes were pertinent in the drive to increase field exposure and particularly in the case of the head coach, a clear directive to push physical standards. Previous research has shown coach change is linked with a 2.3-fold increase in muscle injury rate (5.3 injuries/1000 hours of exposure) in an elite soccer club (Domnez et al., 2018) and training load was discussed as a changing factor. The observation was that the newly hired coaches tend to be critical of the approach of their predecessor resulting in a boost in training intensity (Domnez et al., 2018). Results from this study saw a change in load following coach changes epitomised by the increase in volume load in the preseason of season three with the change in head coach. Coach change often comes after consistent poor result in-season which would lead to a new training philosophy being implemented during the competition cycle. The changes highlighted in this study saw the changes made during off-season so the new coaches were able to implement their training programmes across the pre-season.

The elite sporting team participating in this study had a high amount of player turnover impacting the ability to obtain a full description of each players training history. Sampling from only one team prevented the examination of non-linear effects of age and training load on injury risk. This study was able to include many of the commonly used training load measures however there are others such as distance covered in relative speed zones that were not available that may contain relevant information. Presenting longitudinal changes in components can be interpreted in different formats. Figure 5.3 presents data from this study to highlight patterns across three seasons however, research using data from a cohort of rugby players present a time series plot method utilising standard deviation zones to highlight variation across two seasons (Weaving et al., 2019). An example of this method used on data from the current study is shown below in Figure 5.6 which could be subsequently explored for further use.

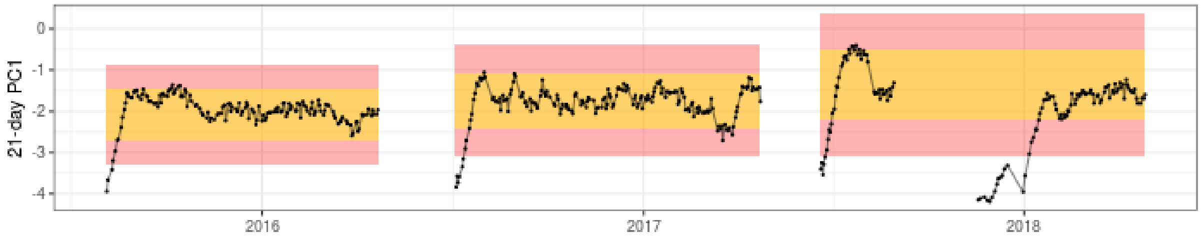



*Figure 5.6 Rolling 21-day average volume load scores compared to the pooled mean and SD for all players*

It is also important to consider the potential effects of the change in technology used between season one and the subsequent seasons. The main changes to the new hardware provide to elite clubs by STATSports included an improved accelerometer sample speed and importantly a GNSS-enabled chipset allowing for enhanced satellite availability. Practitioners have to consider the effects of changes in both hardware and software, especially when analysing data longitudinally.

### *5.6 Practical applications*

- Principal component analysis can provide a simpler (lower dimensional) representation of training load that has associations with injury risk.
- The findings of this study provide insight into statistical analysis of training load that are inclusive of relevant information, thorough in statistical methodology and considerate to the coach-practitioner relationship.
- Conscious manipulation of training loads over an extended multi-season period may be able to influence team injury rates in professional soccer.

### *5.7 Conclusion*

The main findings of this study are that a higher accumulated training load during pre-season resulted in a longer estimated period before in-season injury incidence. The effect of pre-season injury (sessions missed) and age shows no clear trend with a higher in-season injury rate. A principal component analysis was used identify three training load components (volume load, speed load and density load) to represent commonly collected metrics to propose a method of data analysis to streamline communication and maximise training load decisions. Future research should aim to sample data across multiple teams and explore the use of PCA to streamline additional data sources including internal metrics, testing and screening along with data coming in from new technologies as they are introduced into a soccer club's monitoring process.

# CHAPTER 6: PREDICTIVE MODELLING OF TRAINING LOADS AND PERFORMANCE IN ELITE SOCCER

## *6.1 Chapter summary*

A key theme throughout this thesis is the focus on applied practice carried out in elite soccer clubs. The studies leading up to this point have investigated the technology used to monitor training and match load, explored the methods that data is processed and investigated associations between training load with injury incidence.

The final study tackles the challenges of firstly measuring soccer match performance and then using statistical models to estimate performance. A holistic performance metric (InStat Index) was selected and correlated against a successful performance outcome measure indicating a high individual index is favourable for team success. The index was used as the performance metric in five forecasting models, scaling up in complexity, with the final two that considered training load (Banister training-impulse). The results of this study showed that InStat Index is a useful metric that can be used by coaches and practitioners to quantify match performance individually. Results from the forecasting models indicate that the use of training load metrics is no better than simple methods of forecasting match performance. The best performing model produced an error of 9.5% and differences between model performance were minimal. It is unlikely that in the applied setting, coaches would make decisions based on the error associated with current models however; future research with access to larger data sets from various data sources impacting performance could yield stronger results.

### *6.2 Introduction*

The quantification of individual actions performed by soccer players during matches and the contribution of these actions to team success remains largely unexplored (Decroos et al., 2019; Pelechrinis et al., 2019). The low-scoring and dynamic nature of soccer complicates analysis leading to a dearth of performance-related questions close to the 'language of the game' that can be answered through analytics (Fernandez et al., 2018).

Conversely, the physical output of soccer players during training and match play are well-documented (Bangsbo, 1994; Stølen et al., 2005; Bradley et al., 2010; Varley and Aughey, 2013; Barnes et al., 2014; Ingebrigtsen et al., 2015). Electronic Performance and Tracking Systems (EPTS) are technologies used to track player position to infer the output of training and match-play. Examples include optical based tracking systems that use high speed cameras within stadiums, local positioning systems that utilise fixed receivers for position data from a unit worn by players and pertinent to this thesis, GNSS devices calculating position data (FIFA.com, 2019). These data provide useful information to identify the current physical demands placed on players in competition (Bradley et al., 2013) and for practitioners within soccer clubs to plan position-specific periodised football training (Serpiello et al., 2011; Ingebrigtsen et al., 2015).

Periodisation in soccer encompasses the strategic manipulation of training stress to produce a desired outcome. The desired outcome in elite soccer teams is to maximise squad availability while optimising player readiness for matches, ensuring that each player has the physical capability to implement the required tactics successfully (Walker and Hawkins, 2017). A well-planned progressive training programme with variation in frequency, duration, intensity, and type of activities should be implemented to aid these goals (Jaspers et al., 2017). To support this process, training load is monitored to make evidence-based decisions on appropriate loading schemes to enhance desired success outcomes (Akenhead and Nassis, 2016).

The recent use of match performance metrics to link physical performance (Modric et al., 2019) and the above-mentioned body of research on physical performance in training and match play opens up the avenue for research to go further to investigate the association with performance measures. The ability to forecast outcomes such as performance, talent, or injury is arguably the field of sports science and medicine modern-day equivalent of the 'Quest for the Holy Grail' (McCall et al., 2017). Mathematical modelling has been used in a variety of sports to attempt this process. Pertinent to this study, the Banister impulse-response model (Banister et al., 1975) quantitatively relates performance at a specific time to the cumulative effects of prior training load (Taha and Thomas, 2003). Originally conceived to model swimming performance (Banister et al., 1975), the model has used training load to predict performance in various sports including swimming (Hellard et al., 2005), cycling (Busso, 2003) and running (Morton et al., 1990; Wood et al., 2005).

A significant challenge for practitioners and researchers is deciding on a performance metric to analyse match-day technical performance. It is suggested that methods incorporating several facets of the game, within a dynamic context, would appear to be superior and most appropriate for use (Ali, 2011). Coach rating scale is an example of a subjective performance measurement (Cormack *et al*., 2008; Mooney *et al*., 2013; Rowell *et al*., 2018) which relies on standardisation on feedback timing and a reliance on coach ability to block emotion and bias from rating decision. Objective proprietary metrics have been created using a combination of measured metrics from event data that measure effective and ineffective skill execution throughout a match (Champion Data impact ranking system) (Mooney et al., 2011; Sullivan et al., 2014; Lazarus et al., 2017). These metrics are used to guide player transfer decisions, understand positional values and estimate the expected player contribution translated in units with which managers and fans associate (Fernandez et al., 2018; Pelechrinis et al., 2019; Decroos et al., 2019).

In the current landscape there is a plethora of organisations which are using the explosion in technology development and pushing the boundaries in data analytics in this area which in turn expand the opportunities for performance metric in team sports. Champion Data, Opta and InStat are example companies that developed through a desire for performance data from sources including media, betting companies, fans and pertinently sports teams (Opta, 2018).

InStat have created a unique algorithm which follows the holistic principles of the combination metric providing a-rounded assessment of player performance (InStat Index - InStat, Moscow, Russia). This automatic algorithm considers the contribution of the player to team success, the significance of their actions, opponent's level and the level of the championship they play in (InStat, 2019). The index was created to speed up the scouting process, assess the player actions considering the opponent and competition level, compare players on different positions and reflect a player's performance in match periods and longitudinally. InStat Index was recently used in a study as a holistic match performance indicator to analyse the association between running performance and match performance (Modric et al., 2019). The use of these indices to estimate performance and comparing them to other metrics such are training load is yet to be investigated.

This study tackles the challenge of metric selection to measure soccer performance and then explores the value of estimating performance. More specifically the aims are: (1) Establish whether InStat Index can be used to measure soccer team and individual player match performance, and (2) compare the success of forecasting models to estimate performance; specifically, to assess the value of using training load.

## *6.3 Methods*

### *6.3.1 Data collection*

Training load data was collected from 56 male elite soccer players competing in the highest level of competition in Australia (mean ± SD age at first record - 22.6 ± 5.4 years). Players were monitored for three seasons, resulting in 86 player seasons of data collected and 11,141 total training and match observations.

As described in Chapter 5, all players wore commercially available devices during all field-based training sessions and matches. Devices available for use during season one were GPS-enabled (10-Hz) and accelerometer (100-Hz) devices (Viper 2, STATSport technologies, Newry, Northern Ireland). Devices worn during season two and three were GPS-enabled (10-Hz) and accelerometer (600-Hz) devices (Apex, STATSport technologies, Newry, Northern Ireland). Research has highlighted the limitation of the devices used in season one but has justified it's use to measure team sport-specific movement (Chapter 3; Coutts and Duffield, 2010; Beato et al., 2016; Scott et al., 2016). Apex devices have shown good levels of accuracy (bias < 5%) in sport specific metrics and can therefore be used to quantify players' workload during training sessions and to optimise the overall training periodisation (Beato et al., 2018). Shown in Chapter 5, data lost due to unit or user error (172 observations – 1.54%) were estimated by using an individual average for that subject referenced to the session type (highlighted in Figure 5.4).

Soccer performance was quantified using a proprietary player rating metric (InStat Index, © InSstat, Moscow, Russia). A player's rating is calculated as a weighted sum of actions where the set of actions and weights are position specific. The explanation from InStat clarifies; '*InStat Index is calculated in every match based on the following indicators - quantitative indicators of player's actions in the game (specific for each position), as well as the weighted match level coefficient that takes into account the player's level, and the levels of his team-mates and opponents'*. Ethical approval for this research was obtained from the University of Bath 'Research Ethics Approval Committee for Health' (REACH - reference number: EP 11/12 129). Signed subject consent was obtained from each player for analysis and publication of de-identified data.

### *6.3.2 Relationship between InStat player ratings and match performance*

To assess the applicability of using the InStat Index to rate player's performance between 2015-2017 seasons in the professional Australian soccer league; for each match (n=228), the difference between the total InStat Index accrued by each team was compared to the goal difference and expected goal difference (xG). xG is currently the most prominent commercially available metric used in elite soccer event data analysis focussing on the team's ability to create chances and the subsequent quality of those chances. It takes into account the build-up, the context of a shot (e.g., location, number of defenders in the vicinity etc.) and the probability of the chance leading to a goal (Pelechrinis et al., 2018). The strength of relationship between InStat differential, goal difference, and xG difference was assessed using the Pearson correlation coefficient.

*6.3.2 Estimation of player performance*

Multiple methods were compared for estimating the performance $p_{g,i}$ of a player $i$ in a match $g$ (Table 6.1). Models were restricted to only use information collected before a match. The first four observations of match performance for each player in the dataset were excluded to allow for model 4 and 5 parameters to have enough data to fit.

| Model | Description |
|---|---|
| 1 – Previous match | The simplest baseline model considered was to forecast the performance of each player to be the same as their previous match. |
| 2 – Performance average | Forecast for each player is their average InStat rating in all their previous matches in the dataset |
| 3 – Team average | Forecast for each player is the average InStat rating of all players in all previous matches in the dataset |
| 4 – James-Stein estimate | Forecast for each player is their average in all previous matches, with an adjustment to shrink the value towards the average of all players (Efron and Hastie, 2016) |
| 5 – Banister impulse response model | Impulse response models were fitted for each player. Two training load impulse variables were considered; total distance (TD) and high-speed running distance (HSD) $$p_{g,i} = p_0 + k_1 \sum_{j=1}^{i-1} w_j e^{\frac{-(i-j)}{t_1}} - k_2 \sum_{j=1}^{i-1} w_j e^{\frac{-(i-j)}{t_2}}$$ |

$p_{g,i}$ – Performance (InStat Index) of player i in match g
g – Match index
$p_0$ – Initial performance level
$k_1$ – Magnitude of fitness response to training impulse
$k_2$ – Magnitude of fatigue response to training impulse
$t_1$ – Fitness curve time decay constant
$t_2$ – Fatigue curve time decay constant
w – Training impulse i.e. TD (m), HSD (m > 19.8kmph)
$i$ – Player index

*Table 6.1: Player performance forecasting models*

The difference between the predicted and actual InStat performances for each player-match (n=1227) were calculated for each model. Models were compared by calculating the median and inter-quartile range of the absolute prediction errors for each player-match. Additionally, relative model errors were calculated by expressing the absolute error as a percentage relative to the average InStat score across all player-match observations.

It was proposed to use the three new monitoring components produced from the principal component analysis of training data in chapter 5 (volume load, speed load and density load). Unfortunately, the output from these components are not applicable for use with the Banister model due to negative values. If you input a negative training dose into the Banister model all of the responses get flipped (i.e. "fatigue" increases performance and "fitness" decreases it). Total distance was selected to represent total volume (correlation value of 0.948 for volume load) (Table 5.1) and high-speed distance to represent speed exposure. As outlined in Chapter 5, HSD has been linked with hamstring injury (Askling et al., 2013) but more pertinently to this study there has been a significant increase in HSD match demands therefore outlining the importance of the training regulation of this physical metric (Barnes et al., 2014).

All analyses were performed using the R statistical programming language (version 3.5.1) (R Core Team, 2018) utilising ggplot2, dplyr and cumstats as the principle packages.

## *6.4 Results*

### *6.4.1 InStat Index to quantify soccer performance*

The relationship between the difference in total InStat Index and match outcomes are shown in Figure 6.1. Data are from all matches of a club competing in the Hyundai A-League from 2015-18. InStat Index descriptive data is shown in Table 6.2 highlighting the typical scores achieved by elite soccer players across different playing positions. The correlation between InStat Index differential and match outcomes (r = 0.78 and r = 0.54) suggests that accruing a higher total InStat Index score than the opposition is generally a favourable outcome.

| **Position** | **n** | **InStat Index (Mean±SD)** |
|---|---|---|
| Centre Defence | 234 | 220.9±11.1 |
| Wide Defence | 206 | 216.8±16.4 |
| Centre Midfield | 296 | 221.2±19.5 |
| Wide Midfield | 194 | 216.3±17.9 |
| Centre Forward | 116 | 235.1±18.4 |
| Average | 209 | 221.9±16.6 |

*Table 6.2: InStat Index descriptive data*

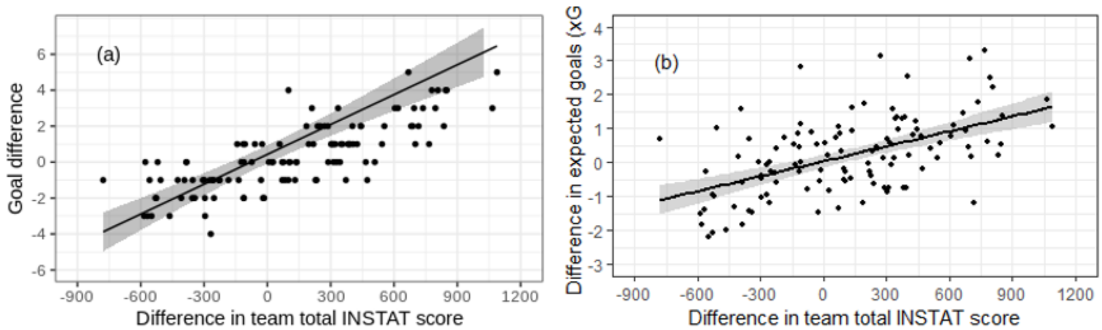



*Figure 6.1: Relationship between team InStat Index score differential and (a) match goal difference, (b) expected goal difference.*

*6.4.2 Comparison of forecasting methods*

The median and interquartile range of InStat Index forecasting errors for each model is shown for absolute error score (Figure 6.2) and error percent relative to the average InStat Index for all players and all matches (Figure 6.3). The most accurate estimates (lowest absolute and relative percentage error) of a player's future match performance were from the James-Stein estimate (InStat Index error 21.5, relative error percent 9.5%) and by taking that players previous average (21.7, 9.6%). Performance forecasting based on the use of the most recent previous match had the highest median error (30.0, 13.3%). Using training load information and a banister impulse-response model to forecast match performance did not improve on the simpler methods (26.8, 11.9%), and showed relatively high variability (large IQR). It is important to note that although the above inferences can be made, the differences between model performance is low.

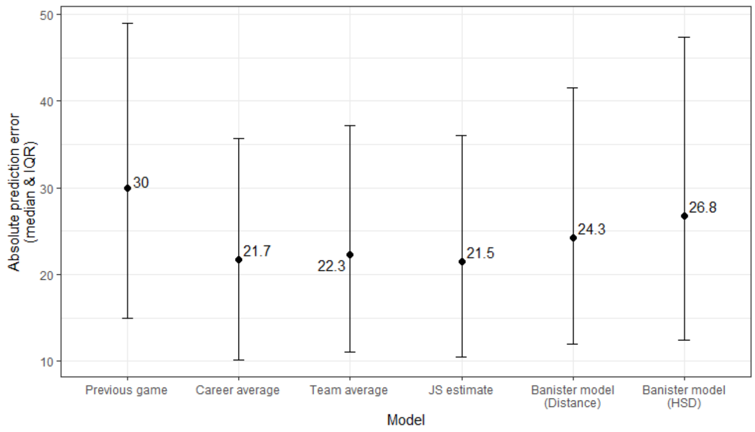



*Figure 6.2: Median and interquartile range of InStat Index prediction error (absolute) for each forecasting method.*

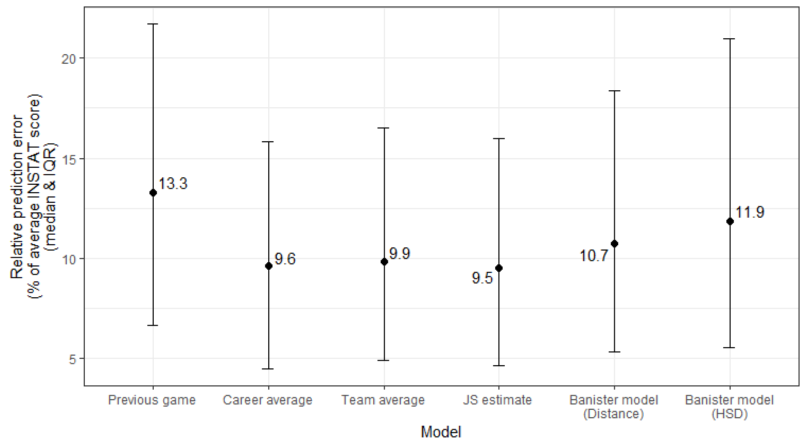



*Figure 6.3: Median and interquartile range of InStat Index prediction error percentage (relative) for each forecasting method.*

Figure 6.4 shows how the accuracy of InStat Index performance estimation methods changed as a player accumulated more match performance observations in the database for the best performing model (James-Stein estimate) and the two Banister models (using distance and high-speed distance training load input). At the beginning of a player's match history the Banister models showed higher error than the James-Stein estimate. Once a player accumulated 30 or more match observations (i.e. the models were being fitted to over 30 observations) the Banister models showed a decreasing trend in error although throughout the match history which include an error increase again after 60 observations, there is a noteworthy overlap of the inter-quartile ranges. The error for the James-Stein estimate remained relatively constant throughout the player's match history.

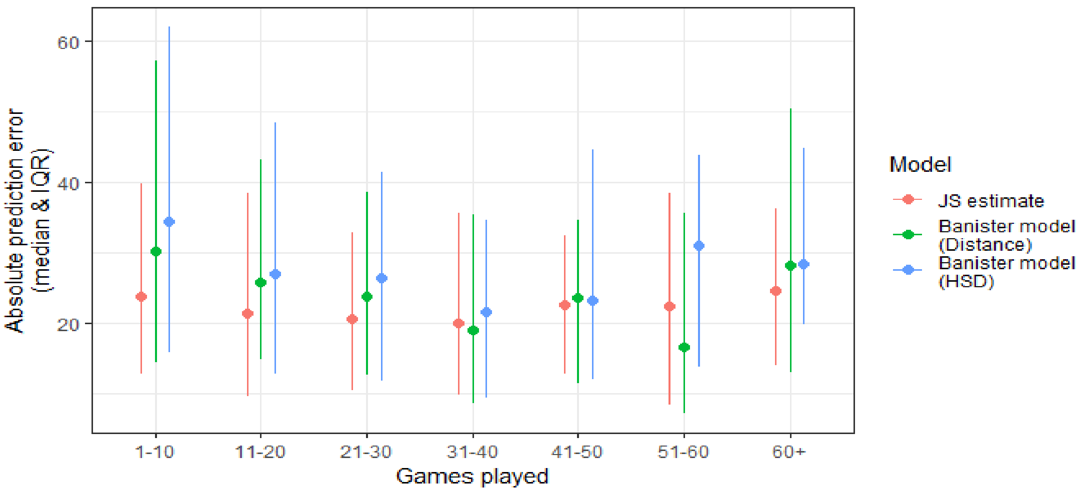



*Figure 6.4: Variation of InStat Index prediction errors for different amounts of player match performance observations.*

*6.4.3 Distribution of fitted Banister parameters*

Banister's model was used to apply training load metrics to forecast future performance in order to address the second aim of this study. This section will specifically evaluate the model used in order to further understand the effectiveness to estimate performance. The distribution of Banister model parameters ($k_1, k_2, t_1, t_2, p_0$) is shown in Figure 6.5. The vertical axes have been cropped to include 95% of all observations, the most extreme 5% distort the scale beyond interpretation (e.g. values in excess of 106 for $t_1$). Figure 6.5 shows large variability in the fitted parameters, that tends to decrease as the number of match observations for a player increases. The parameters $k_1, k_2$ showed a tendency to approach zero, whereas trends in the other parameters were unclear.

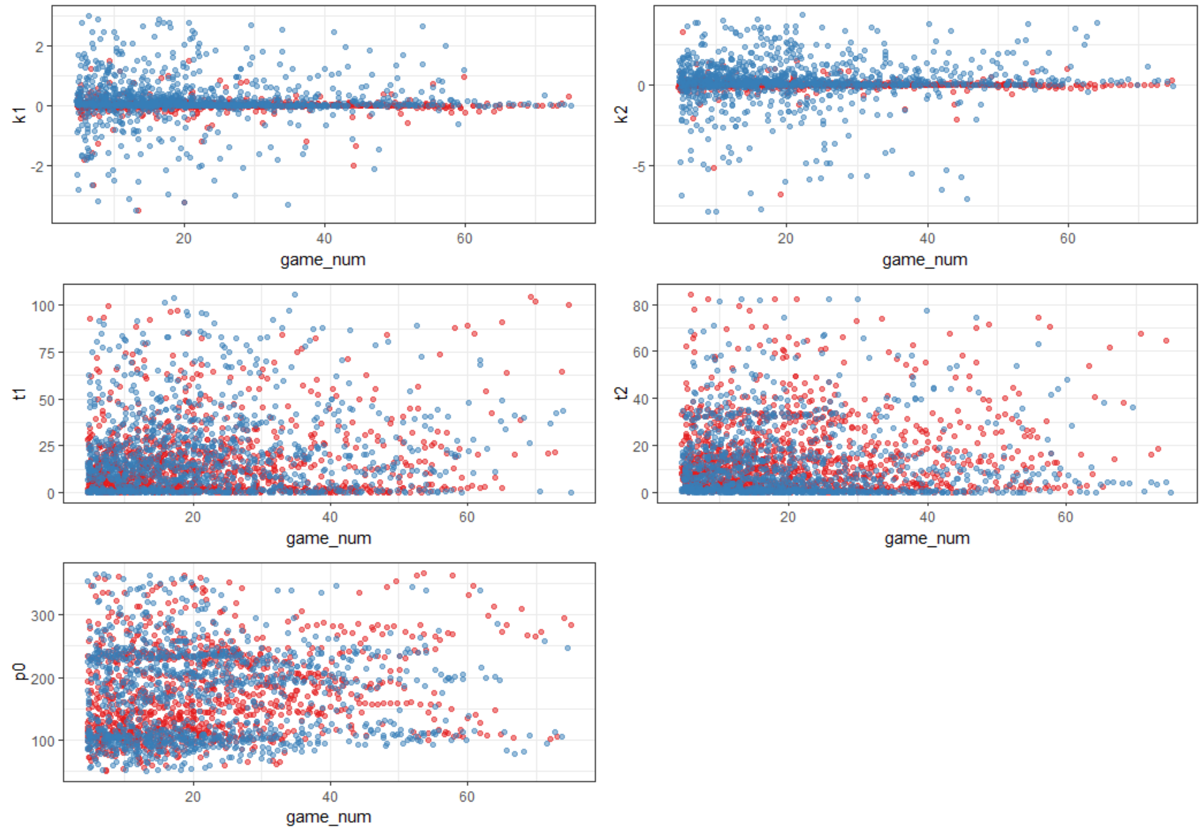



*Figure 6.5: Distribution of banister model parameters as the number of player matches increases (red = distance model, blue = high-speed distance model). Axes have been cropped to include 95% of all values.*

### ***6.5 Discussion***

The first aim of this study was to establish whether InStat Index can be used as a metric to measure soccer match performance and to then use this holistic metric to compare the success of forecasting models to estimate performance. The models increased in complexity but there was very little difference in model performance and subsequent error. Training load was unable to offer any more insight than the simple forecasting models.

#### *6.5.1 InStat Index to quantify soccer performance*

Measuring match performance in soccer is complex and it is suggested that analysis methods that incorporate several facets of soccer, within a dynamic context, would appear to be superior and most appropriate for use (Ali, 2011). This study showed how a holistic event data metric (InStat Index) was correlated with team success and it can be therefore considered that if a player obtains a high InStat Index for their match performance that this is indicative of higher soccer performance and more likely to yield success. The correlation between performance metric and team success was utilised in a previous study using an internal multifactorial concept against team ranking across six professional soccer leagues (Pappalardo and Cintia, 2017).

The index was correlated to goal difference (ultimately shows result) and xG (chance quality) to compare it against known team success metrics. The result, shown by goal difference, is the ultimate gauge of success; however, it may not tell the true story of individual or team performance due to the complex nature of the sport. Breaking down the match into the event data provided, allows coaches and analysts to assess individual contributions to team success. The correlation to xG is not as high and this could be due to the principles behind the metric calculations. xG is offensively bias whereas the index is specific to position across the whole pitch. It is calculated using a unique algorithm using specific metric relevant to each position and also considers the contribution of opponent and competition level. This study is in agreement with previous research (Modric et al., 2019) that InStat Index is an appropriate metric to measure individual player match performance in elite soccer.

### *6.5.2 Selection of models and metrics*

InStat Index was established to estimate player performance through a hierarchy of models. Heuristic techniques were selected first and complexity then added in layers as models progressed to investigate the success to forecast performance. Banister's impulse-response model was selected as the final model to investigate how training load can influence the estimation of performance over much simpler forecasting models. Banister's model estimates performance, indicated by InStat Index, at a specific time to the cumulative effects of prior training load (Taha and Thomas, 2003) measured in this study by two volume-based metrics (TD and HSD).

A similar study investigating the relationship between estimates and actual match performance indices in professional Australian footballers also used a variable dose-response model with similar physical metrics. Dose response models from multiple training-load inputs can predict within-individual variation of an Australian football specific performance index (Cormack et al., 2018). This study in a different team sport, did not use any other forecasting models so there was no reference to say whether impulse-response models were any better than simple heuristics. Additionally, where the current study used the Banister impulse-response model in addition to other estimation models, this was not an exhausting list and future research could select different modelling methods which could elicit different outcomes.

### *6.5.3 Performance prediction model comparison*

The results showed the most accurate estimates of a player's future match performance were from the James-Stein estimate (9.5%) with the least accurate (highest error) being the simplest model of assuming performance will be the same as the previous week (13.3%). In absolute terms this equates to an improvement of 8.5 index points between the two models highlighting the small differences between the tested models (referenced to the data shown in Table 6.2). The use of training load information performed better than the simplest model but results show all remaining three models (<10%) performed better than the two banister models (TD 10.7%, HSD 11.9%). This also indicates the trivial differences between the forecasting models to estimate match performance.

This study supports previous research (Egidi and Gabry, 2018) that individual player performance is hard to predict. All methods considered had median errors above 20 InStat points. Soccer is such a complex sport and factors from a range of fields including physiology, psychology and pedagogy add to the myriad of intangibles that impact performance. As exposure to different technologies increases and research in a whole variety of areas progresses including the ability to collate these data together, understanding of soccer performance will improve and the ability to predict performance will have impact on training optimisation. The error increase using the Banister model using both distance and high speed distance after 51 observations could be due to a number of factors including the fact that there are fewer players that played that many matches, the players have more variable performance or that their performance is less dependent on training load.

### *6.5.4 Critique of Banister model*

This study used the Banister dose-response model due to the popularity of use in a variety of sports to predict performance from training load (Clarke and Skiba, 2011), its simplicity that performance could be defined by two components (fitness and fatigue) and that at any time their difference can predict an athlete's performance (Borrensen and Lambert, 2009). Despite the attractiveness of the concept, this study is in agreement with previous research, questioning accuracy, stability and goodness of fit (Hellard et al., 2006). This study found that the model parameters k1 and k2, intended to represent the changes in performance from training, tended to converge towards zero. This means that training dose had minimal impact on the forecasted performance levels. The large variability of the estimated model parameters suggested the model was unable to capture a stable relationship between training and performance in the athletes in this study

## ***6.6 Practical applications***

- InStat Index is a holistic match performance metric that can be used by coaches and practitioners to quantify match performance individually based on a correlation to team performance
- Based on current data available, forecasting models including using training load metrics cannot be used to estimate individual player match performance

### *6.7 Conclusion*

The main findings of this study were that the forecasting models implemented were not able to estimate match performance. The use of training load was unable to offer any more insight to performance estimation over simple forecasting models so ultimately, none of the models within the study performed well enough to be a useful practical tool for coaches or practitioners at this current stage. Future research, which has access to larger data sets, across broader areas of player monitoring, utilising ever developing technology and statistical techniques to collate data, could explore further the ‘holy grail’ of performance prediction in elite soccer.

# CHAPTER 7: GENERAL DISCUSSION

## *7.1 Introduction*

The main aim of this thesis was to evaluate new methods of data analysis from an elite soccer longitudinal data set, to provide insight to the association between training load, injury and performance.

The research was conducted over a period of seven years as it was completed in conjunction with working full-time. The length of the research term posed both advantages and disadvantages as working from within the soccer environment meant the questions that were being posed by a varied background of coaches and players with different training philosophies, underpinned and guided the research throughout. This key advantage meant that the research was always held close to the applied setting which was a key focus from the outset. The weaknesses of conducting the research across such a period was that the studies quickly became outdated as technology moved on and philosophies changes. A clear directional change through thesis transfer was to shift to a focus on performance measures to fit with current research and applied practice.

To address the aims outlined in Chapter 1, four studies were conducted, with the final goal of generating relevant and applicable knowledge within elite soccer to enhance the practices within performance departments.

The paragraphs below highlight the main findings from the studies included in this thesis:

1. *Assess the validity of GPS devices to measure the distance of team-sport specific movement.*

The validity of GPS devices for use in soccer was investigated in Chapter 3, and showed a weak linear relationship relative to a gold-standard measure (motion capture system). This study showed that caution is recommended when measuring movement with multiple change in direction.

2. *Provide context to training load data and simplify the description of training by identifying pertinent metrics.*

Dimensionality reduction (Chapter 4) was used to produce three contextualised training load components. The context was applied by collecting match data and using them as training load thresholds. The three new components - ‘change in velocity’, ‘velocity’ and ‘metabolic intensity’ - were named to simply represent the metrics which contribute to their make-up. Collectively, the terms symbolise three key areas of training load which put different physical stresses on the player. This study explores methods of analysing training load in elite soccer for the purpose of applying these principles in Chapter 5.

3. *Provide insight into the statistical analysis of training load used in elite teams*

The reductionist approach described in Chapter 4 was employed to analyse three seasons of training and match data and highlighted a number of methods of presenting longitudinal load (Chapter 5). The study shows that principal component analysis can be used to identify training load components (volume load, speed load and density load) to represent commonly collected metrics to streamline communication and maximise training load decisions in a number of introduced applied concepts (micro-cycle manipulation, seasonal creep and change in coaching staff).

4. *Analyse the influence of training load on the risk of injury in elite soccer players*

The main finding of this study was that a higher accumulated training load during pre-season resulted in a longer estimated period before in-season injury incidence (Chapter 5). Pre-season injury (sessions missed) and higher age did not show a clear relationship with injury incidence. It is important to consider the multiple factors contributing to training load adaptation and injury risk highlighted in Chapters 2 and 5.

5. *Establish whether InStat Index can be used to measure individual match performance*

This study correlated InStat Index, a holistic match performance metric, to goal difference and expected goals, supporting its use by coaches and practitioners to quantify individual match performance.

6. *Analyse the influence of multiple factors, including training load, to assess the subsequent success to predict performance*

Finally, a variety of prediction models were used to predict InStat Index (match performance) in Chapter 6. The main findings of this study were that training load was unable to offer any more insight to performance estimation over simple forecasting models. Importantly, none of the models within the study performed well enough to be a useful practical tool to predict performance highlighting the multifactorial nature of soccer performance.

## *7.2 Overall discussion*

This section of the thesis will discuss the previously highlighted findings from each of the studies completed. An in-depth analysis of the challenges faced, the limitations, practical applications and also potential future research recommendations is included in the below.

### *7.2.1 The validity of global positioning system (GPS) devices for measuring distance of team-sport specific movement*

This study found that 10- and 15-Hz GPS devices overestimated distance of soccer specific movement compared to a gold standard criterion measure (Chapter 3). Carried out early during the PhD (2014), tracking technology has significantly developed with a large priority being accuracy. Today, ETPS providers use standardised testing days operated by FIFA which use many of the same methodological principles used in this study, in order to be accredited for use in elite soccer.

The devices tested (Chapter 3) have been validated for use to measure team sports, with caution recommended with increased speed, acceleration and changes in direction (Scott et al., 2016; Malone et al., 2017a). Results agreed with this body of literature, and showed that the accuracy was best during unidirectional movement with simple change in direction and decreased with trial complexity (i.e. ZIG). It is suggested that accuracy decreases due to the increased complexity of the movements and the inability of the devices to compute the small changes in body position. There were also large differences found in accuracy between manufacturers, which could be due to factors such as sampling frequency, chipset or data processing algorithm variation.

A key strength of this study was the use of an optoelectronic motion capture system as the gold standard measure. An early challenge to the research was to ensure that this, then lab-based system, could be taken to an appropriate outside space for soccer specific movement testing, allowing for clear satellite signal. Chapter 3 outlines how the system was configured and then calibrated to accuracy of 2.6mm to ensure the criterion measure stood apart from previous validity trials. The current protocol used by FIFA to certify ETPS also measures soccer specific movement using a motion capture system as the gold standard measure.

One of the main limitations to this study was that satellite number and HDOP data were not available due to the device versions tested. Current GNSS devices can provide this data readily within the software as easily as load-based metrics. Checks were made to ensure that there was a complete data trace on all trials with the absence of any abnormal ‘spikes’ which can be caused by a number of conditions highlighted in Chapter 2.3. At this point of the study, the devices only had access to the American GPS as they were not GNSS-enabled, which meant reduced satellite availability. The developed devices used during data collected in Chapter 5 and 6 were GNSS-enabled. Chapter 2.3 also explains the effect of GNSS satellite availability.

Additionally, there is limited trial data collected, especially for Minimax and SPI devices. This was due to only having one device available from each of these manufacturers. Trials were also discounted if there were issues with Qualisys data for example, marker drop out, damaged files or missing sections of trial data. To conduct a robust comparison of the difference between manufacturers, more data would be recommended.

Future study could overlay raw positional data values from both Qualisys and GNSS devices, potentially using methods such as statistical parametric mapping (SPM). SPM was originally developed for the analysis of cerebral blood flow in 3D PET images (Worsley *et al*., 1992), but has been used more widely in a range of biomechanical applications (Pataky, 2010). Some studies suggesting the investigation of x, y data to assess validity can provide accuracy insight into position accuracy; however, applied practitioners are not currently using coordinate data to analyse workload. This could be a future method explored with the influx of data scientists, however, as per FIFA protocol, it is appropriate to assess the output produced by GNSS devices and subsequently used day-to-day by practitioners. Another area of future study could explore the error in relation to other frequently measured metrics collected by GNSS devices to guide training load. Access to manufacturer equations and algorithms would be critical in this process in order to measure raw error rate and translate it to mechanical error. Metabolic metric accuracy would be an interesting area to explore.

Regarding practical recommendations from this study, the overarching message is that previously, practitioners needed to conduct internal accuracy trials on technologies used in order to appreciate any error associated with the data collected, as many manufacturers would put devices to market before external validation. Where this is still recommended, especially specific to the internal metrics analysed, the standardised certification process adopted by FIFA has meant practitioners can be confident they can invest in a monitoring product that is fit for purpose and safe to use.

This study fitted well into the journey as it was the first study conducted, reinforced the key research principles by going through ethics procedures, carrying out field testing, statistical analysis and study write up. It allowed for a deeper understanding to the history and development of the technology that the thesis is based and offer interesting experiences to other technologies used to measure movement. The take home message was that the first impressions of use in the applied setting and also during testing were the devices used in the trial providing useful and accurate data. The statistical analysis shows the areas of improvement the technology needed, particularly as movement complexity increases, which are being consistently addressed and developed.

*7.2.2 The use of dimensionality reduction to describe training load metrics in elite soccer*

Match data was used to give context to training load to improve communication of data output between the practitioner and the coach (Chapter 4). Following that, it demonstrates how dimensionality reduction can be used to produce three training components that collectively represent key areas of physical training stress. This novel approach to training load analysis was applied using a new data set to investigate three seasons of training and match data (Chapter 5).

The initial findings from this methodological study highlighted the movement demands of soccer match-play. In agreement with previous research, these data can be used to inform practitioners of match demand to objectively show the output players need to be prepared for to aid subsequent planning of training.

This study used match average data to initially address the issue of training load communication. As mentioned in Chapter 5.6, Coutts, (2014) states the ability to effectively communicate training load data is paramount – data should be competently analysed and translated into clear, practical messages. Using the match-training load percentage calculation (Chapter 4.2.3), contextualised load metrics can resonate with coaches and players therefore increasing the potential opportunity for positive data communication.

The secondary and main outcome of the simplification process was to propose a new methodology of metric use to reduce a complex training load analysis process into a simple and streamlined process. Dimensionality reduction was therefore used to streamline twelve load metrics into three new load components which can be utilised in different ways. The newly developed methodology was applied so that other practitioners could use it with any training load data set (Chapter 5).

This study was a methods based study to explore ways in which data can be processed and presented with the aim of providing methodological principles to take forward and use on an applied, longitudinal data set (Chapter 5). The study only looks at a limited number of data process methods and there is increasing research presenting alternative methods for example, using population mean and standard deviation (Bacon and Mauger, 2017), quartiles (Malone et al., 2017) or creating categories using z-scores (Bowen et al., 2017). It is important to acknowledge the multitude of methods available to practitioners for this process, this study present two main ideas but importantly the overarching principle of contextualisation and simplicity for the end user.

*7.2.3 Season-to-season training load change in elite soccer*

In Chapter 5, dimensionality reduction was implemented to provide a simpler representation of training load across different seasons. The three seasons of training and match data from Australian elite soccer, reduced to three training components, were used to describe seasonal changes in load, changes in micro-cycle periodisation and the association that training load has with injury risk.

As discussed previously, the ability to effectively communicate training load data is paramount, so the decision was taken to use dimensionality reduction on the new data for this study. The statistical process outlined in the section 5.2.3 was successfully used to reduce the multitude of training metrics available into three new components, whilst still explaining 88.2% of the variance. Principal component one, named volume load, strongly correlated with distance, session duration, and HMLD and explained 67.6% of the variance. This can be a useful component for practitioners to monitor total player load due to its holistic nature which is accumulated through session time. A simple explanation of this component of training to coaches and players is that it represents an overview of total workload, always referring back to volume. Principal component two, named speed load, correlates with metrics exposing distance covered at higher speeds. This is useful for practitioners, as monitoring exposure to high speed load has been linked with both match physical performance and injury reduction. The explanation of speed load can outline the work completed at high speed often when players have the distance and pitch space to express this physical attribute. Principal component three, named density load, correlated with metres per minute, distinguished by relative distance and can therefore be explained as a representation of the intensity of load.

Using these new components, the main findings of this study were that higher accumulated training load (volume load, speed load and density load) during pre-season resulted in a longer estimated period before in-season injury incidence. This contradicts previous studies in the literature (Hulin et al., 2016) which caution against high load in team sports, but is certainly in agreement with recent research showing training hard and consistently is protective of injury (Hulin et al., 2015; Veugelers et al., 2015; Stares et al., 2017; Gabbett et al., 2018). Risk of injury occurrence in soccer is multifactorial and previously discussed research shows two main indicators being previous injury and older age. The effect of pre-season injury burden on in-season injury rate was analysed to isolate this factor from the training load effect on injury rate. However, the protective effect of increased pre-season training load (Figure 6.5) is not mirrored by the effects of injury burden (sessions missed due to injury) during the pre-season period. Previous research recommend caution when implementing training and match load in older players (Hagglund et al., 2007; Ekstrand et al., 2011), however the results from this study show no clear association between players with a higher age and in-season injury.

A limitation of this study is sample size as, although data was collected over a relatively long period, only one squad of players was monitored and the injury incidence within the study period was low. It is important to accept the potential effects of the change to device version as improved hardware became available. Practitioners should be mindful that whilst manufacturer-recommended upgrades in device firmware will improve certain operational aspects (e.g. bug fixes), they may also affect data output, and thus interpretations of longitudinal data (Varley et al. 2017).

Future research with access to training load and injury data from multiple teams could elicit further findings. The principle component analysis method used to produce simplified load components could also be applied to a range of research designs for example the optimisation of training loads through pre-season (Carey et al., 2017) which modelled distance covered and high speed running to produce feasible training plans that maximise projected performance and satisfy injury risk constraints. Further to this, a machine learning approach may be best suited to analyse the association and prediction potential of training load and injury in soccer. Vallence et al., (2019) highlight a construct aggregating data sources including GNSS data can use various machine learning techniques. Dimensionality reduction could be investigated as part of this process.

Much of this research highlights the need for simple presentation of data to players and coaches but it is also essential for the data management and organisation to be smooth and efficient. EPTS companies are constantly developing their software to accommodate new metrics and it would be useful for practitioners to be able to firstly run a PCA analysis on their own data set within their own platform and then subsequently the new components be part of the daily output.

It would also be interesting for future study to assess how elite teams are adapting to this type of research and if there is change to the age profile of playing squads to increase training and match robustness. Other research could investigate whether these results are reproduced in a different soccer leagues where training modalities and match demands maybe different.

*7.2.4 Predictive modelling of training loads and performance in elite soccer*

Training load was unable to offer any more insight to performance estimation over simple forecasting models. In addition to this, none of the models within the study performed well enough to be a useful practical tool to predict performance.

The study correlated a holistic metric of match success for practitioners to use to measure individual match performance. This study and other previously discussed research highlights how soccer performance is extremely hard to measure and therefore predict, due to its multifactorial nature. Throughout this process, a number of metrics were investigated but the main conclusion was the need to be holistic, position specific and available on an individual player level. A common limitation of these holistic metrics were the bias towards attacking actions and many only accommodating team performance data. When practitioners select performance metrics it is important to be considerate of the above suggestions but also ensure that the selection is specific to the way that the team plays. As describe by Bradley and Ade (2017), an integrated approach contextualizes match demands by assimilating physical and tactical data effectively. This process is still to be truly established and could derive from coach-practitioner interaction to establish team game style, perception of good and bad performance, and then matching event data to these actions. Bespoke and holistic performance metrics could potentially be developed using processes similar to that of InStat Index and subsequently correlated against success factors using the processes exampled in Chapter 6.3.1. This approach was also used to investigate the relationship between performance (measured by an internal multidimensional concept) and final ranking (Pappalardo and Cintia, 2017).

It was planned to use the load metric components developed by dimensionality reduction (Chapter 5) as inputs to the Banister impulse response model. Unfortunately, the new components were unable for use in the prediction model (Banister) because if you input a negative training dose into the Banister model, all of the responses are transposed (i.e. "fatigue" increases performance and "fitness" decreases it).

As discussed, the prediction models did not perform well enough to be a useful practical tool to predict performance which could be due to the size and lack-of-diversity in the data set. Future investigation with a larger data set could show stronger results; however, it is likely that the 10% error is appropriate due to the aforementioned multifactorial nature of soccer performance. Future research with access to larger data sets and importantly, from various data sources, with the increase in technology and data availability, could yield stronger results.

This study first explored how soccer performance is measured and highlighted the advantages of using holistic metrics however further research could elicit further insight into the complex process of quantifying match performance. Soccer performance is so complex and the number of affecting factors including match conditions (surface, weather, opposition level, scoreline, tactics), physical factors (training load, match density, gym exposure, injury history, hydration, age) and a wide array of psychological and social factors (mood, media pressure, social support, contract status). This study used a holistic performance metric which assessed position specific event data based performance. Whilst this was shown to have an association with team success so can be used retrospectively to analyse performance of players, the later part of this study shows that by just using training load information, performance cannot be estimated. Analysis that has access to a larger data set which aggregates multiple contextual factors when managing athlete readiness to perform will be an interesting area of future research.

### *7.3 Future directions*

This thesis explored methods to analyse performance and injury in elite soccer utilising data from GNSS devices. GNSS technology has evolved significantly throughout the duration of this research period, and will continue to do so, as will the available methods to assess technology accuracy. It is recommended that the FIFA strategy for standardised testing that has been developed during the period of this research is leveraged to assess technology accuracy in future research. Additionally, just as GNSS technology has evolved, during the same period new devices have come into the market that will offer further analysis potential. The idea of 'invisible monitoring', whereby loads may be evaluated while minimising athlete and practitioner burden, carries high potential. The influx of data that these technologies could provide will also introduce additional metrics to analyse. For future research, the ability to carry out multi-variate analyses across multiple seasons could potentially highlight further insight to the relationship between training load, injury and performance. The ability to do this analysis with significantly higher subject numbers with access to multiple squads could elicit stronger results. It would also be of interest to analyse the differences between competition level, training philosophy (especially between countries) and also the associations in women's and youth soccer. A machine learning approach may be best suited to analyse the association and potential prediction potential of training load, injury and performance in soccer.

Future work could also establish gold standard metrics to measure soccer match performance culminating together the multitude of contextual factors that affect the readiness and ability to perform. Additionally, this work should consider the variation in playing style and performance goals for different leagues and coaches, in particular, the integration of physical (tracking) and technical (event) data.

### *7.4 Thesis conclusion*

This thesis provides understanding of the validity of the measurement and analysis methods relating to training and match load in elite soccer. The aim of this thesis was to present methods to facilitate effective communication between practitioner and coach by streamlining the data analysis and interpretation process. The dimensionality reduction approach produced a simplified data feedback method to increase the ability of load data to influence the training planning process positively. This approach was applied across three seasons of training and match data, and the analysis found that higher accumulated training load during pre-season resulted in a longer estimated period before in-season injury incidence. From a performance prediction perspective, it has been shown that none of the prediction models currently in use performed well enough to be a useful practical tool to predict performance. This is deemed to be due to the fact that individual performance is hard to measure and therefore to predict. This is a pressing need in the research community, as performance optimisation is the ultimate goal in elite soccer.

Overall, this thesis established the validity of devices to measure distance of soccer specific movement and tracked the development of the technology through the study period. It showed that increasing the training load of elite soccer players can be protective of injury and subsequently presented a variety of methods to aid the analysis process; importantly, the simplification and contextualisation of load data.

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